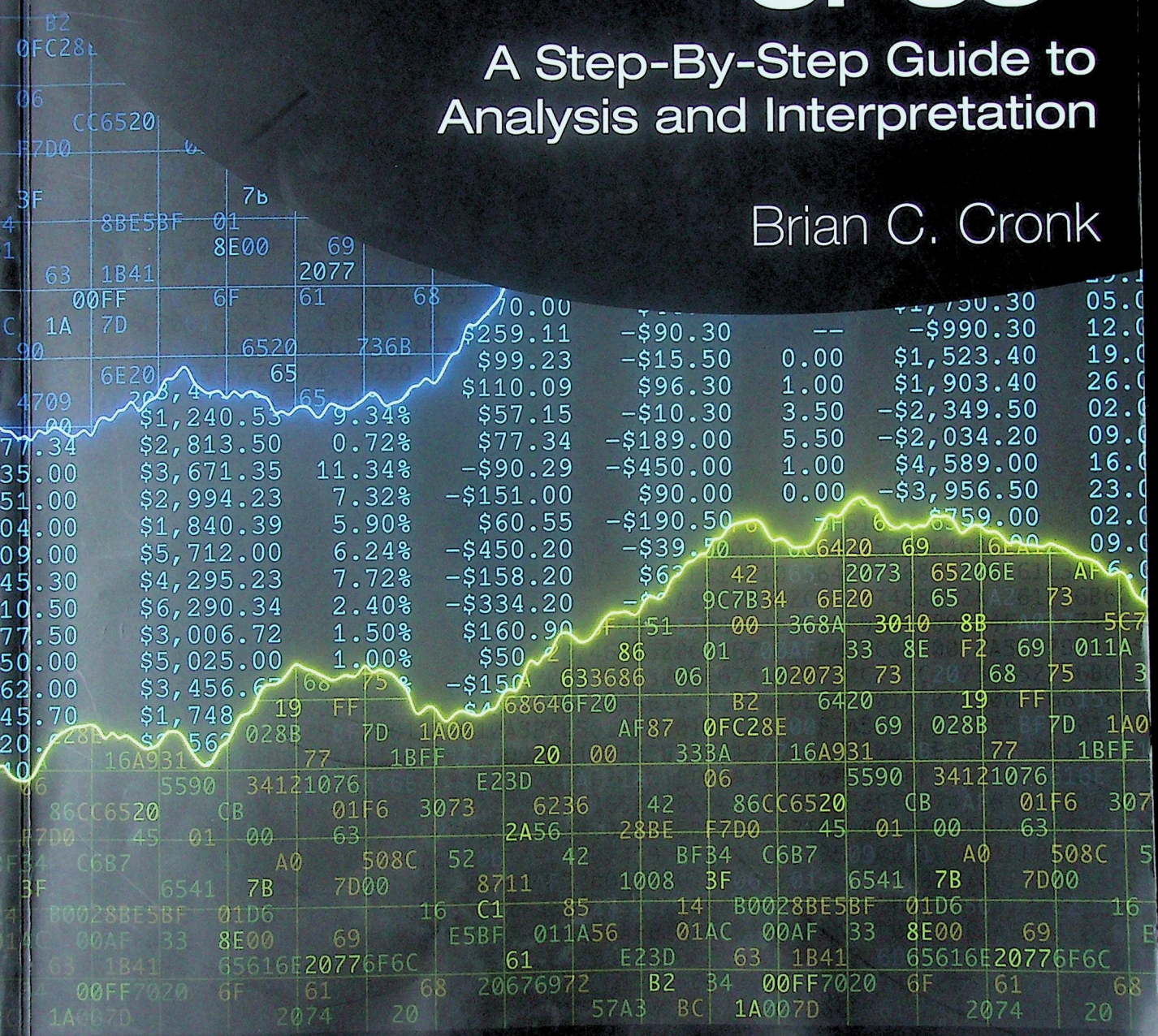


How to Use SPSS®

A Step-By-Step Guide to Analysis and Interpretation

Brian C. Cronk



How to Use SPSS®

How to Use SPSS® is designed with the novice computer user in mind and for people who have no previous experience using SPSS. Each chapter is divided into short sections that describe the statistic being used, important underlying assumptions, and how to interpret the results and express them in a research report.

The book begins with the basics, such as starting SPSS, defining variables, and entering and saving data. It covers all major statistical techniques typically taught in beginning statistics classes, such as descriptive statistics, graphing data, prediction and association, parametric inferential statistics, nonparametric inferential statistics, and statistics for test construction.

More than 270 screenshots (including sample output) throughout the book show students exactly what to expect as they follow along using SPSS. The book includes a glossary of statistical terms and practice exercises. A complete set of online resources including video tutorials and output files for students, and PowerPoint slides and test bank questions for instructors, make *How to Use SPSS®* the definitive, field-tested resource for learning SPSS.

New to this edition:

- Now in full color with additional screenshots
- Fully updated to reflect SPSS version 26 (and prior versions)
- Changes in nonparametric tests Model View incorporated
- Data and real output are now available for all *Phrasing Results* sections – eliminating hypothetical output or hypothetical data

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A Step-By-Step Guide to Analysis and Interpretation

ELEVENTH EDITION

Brian C. Cronk



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Preface to the Eleventh Edition

Introduction

IBM® SPSS Statistics software (“SPSS®”) is a statistical package produced by IBM, Inc. Prior to 2009, SPSS was a separate company and produced statistical software under the SPSS and PASW names. IBM SPSS Statistics is designed to perform a wide range of statistical procedures. As with any other powerful program for the computer, there are certain conventions and techniques that must be mastered for efficient use of the software and to obtain consistently correct answers. By providing detailed, step-by-step guidance illustrated with examples, this book will help you attain such mastery.

In addition to showing you how to enter data and obtain results, this book explains how to select appropriate statistics and present the results in a form that is suitable for use in a research report in the social or behavioral sciences. For instance, the section on the independent t test shows how to state (i.e., phrase) the results of both a significant and an insignificant test.

Audience

This book is ideal as a supplement to traditional introductory- and intermediate-level statistics textbooks. It can also be used as a statistics refresher manual in a research methods course. Finally, students can use it as a desk reference guide in a variety of workplace settings after they graduate from college.

SPSS Statistics is an incredibly powerful program, and this text is not intended to be a comprehensive user’s manual. Instead, the emphasis is on the procedures normally covered in introductory- and intermediate-level courses in statistics and research methods.

Organization

This book is divided into nine chapters plus several useful appendices. The first two chapters deal with the basic mechanics of using the SPSS program. Each of the remaining chapters focuses on a particular class of statistics.

Each chapter contains several short sections. For the most part, these sections are self-contained. However, students are expected to master the SPSS basics in Chapters 1 and 2 before attempting to learn the skills presented in the rest of the book. Except for the skills in the first two chapters, this book can be used in a nonlinear manner. Thus, an instructor can assign the first two chapters early in a course and then assign other sections in whatever order is appropriate.

Appendix A contains a discussion of effect size. Appendix B contains datasets that are needed for the practice exercises interspersed throughout this book. Appendix C provides the sample data files that are used throughout this book. Appendix D provides information on choosing the appropriate statistical test. The Glossary in Appendix E provides definitions of most of the statistical terms used in this book. Because it is assumed that this text is being used in conjunction with a main statistics textbook, the Glossary definitions are brief and are designed to serve only as reminders. Appendix F provides a text-based version of the decision tree on the inside front cover.

SPSS Versions

This text is designed to work with SPSS Version 26, although it should work well for any recent version of SPSS.

SPSS also offers several modules. The screenshots in this text were taken using a “full” version of the software (all modules active and installed). Most institutions have at least the Base, Regression, and Advanced modules installed. With these three modules, or if you are using the *SPSS Statistics GradPack* or *Premium Gradpacks*, you can conduct all of the analyses in this text. If you are using the *SPSS Statistics Base GradPack*, some procedures will not be available. When this is the case, the text will clearly indicate that another product is necessary.

If you have different add-on modules installed, the menu bars shown in the illustrations of this text may be slightly different. If your menu bars look different, or if you cannot locate a menu item for a command presented in this book, it may be that your institution supports different modules. Ask your instructor for additional guidance.

Availability of SPSS

Some institutions purchase site licenses from IBM to provide the software at no charge to their faculty and, sometimes, to their students. If your institution has not purchased a site license, you should still be able to purchase the student version of the software in your campus bookstore at a price discounted for the educational community. Either of these will be a fully functional version of the software intended for your personal use. However, the student version is limited to 50 variables and 1,500 cases. If you need software with more functionality, you can purchase the *SPSS Statistics GradPack* from a variety of sources. A quick Internet search for “SPSS graduate pack” will bring up some choices. Please note that you can generally lease SPSS for a period of a single semester if you would like. You can also purchase a month-to-month license of the IBM SPSS Statistics Cloud product.

Conventions

The following conventions have been used throughout this book:

- Items in **bold** are defined in the Glossary in Appendix E.
- Items in *italics* are either buttons or menus from the SPSS program, or they are statistical symbols.
- Items in ALL CAPITAL LETTERS are either acronyms or the names of variables in the SPSS data file.

Screenshots

Screenshots have been used extensively throughout the text as a visual representation of what is described. In some instances, there may be minor differences between screenshots shown in the text and those on the student’s own screen. For instance, a screenshot captured while working with a dataset that has been previously saved to the hard drive will show the filename and dataset number, whereas a dataset that has not yet been saved will simply show “Untitled” and “[DataSet0].” Because no two Windows computers are configured exactly alike, and because different modules and

software versions can produce slightly modified screenshots, such minor differences are unavoidable.

Practice Exercises

Practice exercises are included for each skill presented. In addition, the skills acquired in this text can be used in practice exercises in other statistics texts or workbooks. In this respect, an excellent complement to this text is *Real Data: A Statistics Workbook Based on Empirical Data*.¹

Acknowledgments

This book is dedicated to the students in my Introductory Psychological Statistics and Research Team courses. While teaching those courses, I became aware of the need for a SPSS manual that did more than simply tell students how to start the program and enter data. I am deeply indebted to Wendy Schweigert at Bradley University, who first showed me the power, simplicity, and usefulness of statistics. I would also like to thank the hundreds of instructors who adopted previous editions of this text and provided me with constructive feedback. Of course, this text would not have been possible without the support of Kate and my children Jonathan and Katherine. A lot has changed since the first edition of this text. My son had just been born as I wrote the proposal for the first edition. By the time you buy this book he will be nearing graduation from a university.

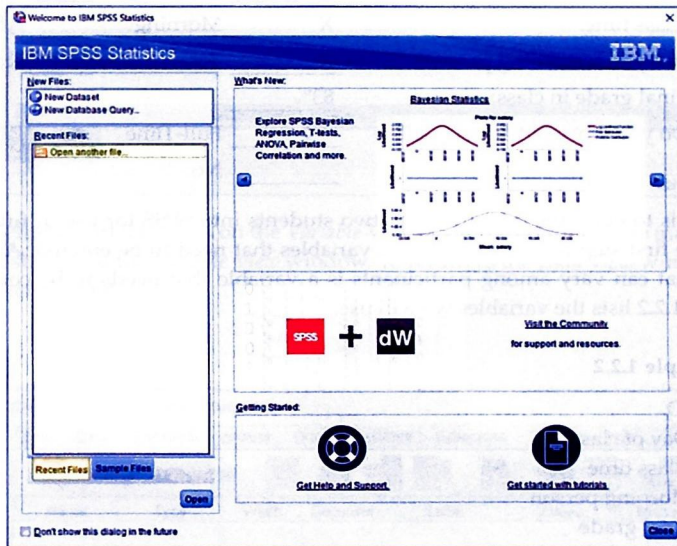
Brian C. Cronk

Chapter 1

Getting Started

Section 1.1 Starting SPSS

Startup procedures for SPSS will differ slightly, depending on the configuration of the machine on which it is installed. If you have difficulty finding it look for an *IBM SPSS Statistics* section of your *Start Menu*. This text uses screenshots from the Windows version of SPSS. The MacOS and Unix versions will have the same functionality, but could appear differently than what is depicted herein.



When SPSS is started, you may be presented with the dialog box above, depending on the options your system administrator selected for your version of the program. If you have the dialog box, click *Type in data* and *OK*, which will present a blank data window.¹

If you were not presented with the dialog box above, SPSS should open automatically with a blank data window.

The data window and the output window provide the basic interface for SPSS. A blank data window is shown on page 3.

Section 1.2 Entering Data

One of the keys to success with SPSS is knowing how it stores and uses your data. To illustrate the basics of data entry with SPSS, we will use Example 1.2.1.

Example 1.2.1 A survey was given to several students from four different classes (Tues/Thurs mornings, Tues/Thurs afternoons, Mon/Wed/Fri mornings, and Mon/Wed/Fri afternoons). The students were asked whether or not they were

“morning people” and whether or not they worked. This survey also asked for their final grade in the class (100% being the highest grade possible). The response sheets from two students are presented below:

Response Sheet 1

ID: 4593

Day of class: MWF X TTh

Class time: Morning X Afternoon

Are you a morning person? Yes X No

Final grade in class: 85%

Do you work outside school? Full-Time Part-Time

 X No

Response Sheet 2

ID: 1901

Day of class: X MWF TTh

Class time: X Morning Afternoon

Are you a morning person? X Yes No

Final grade in class: 83%

Do you work outside school? Full-Time X Part-Time

 No

Our goal is to enter the data from the two students into SPSS for use in future analyses. The first step is to determine the variables that need to be entered. Any information that can vary among participants is a variable that needs to be considered. Example 1.2.2 lists the variables we will use.

Example 1.2.2

ID
 Day of class
 Class time
 Morning person
 Final grade
 Whether or not the student works outside school

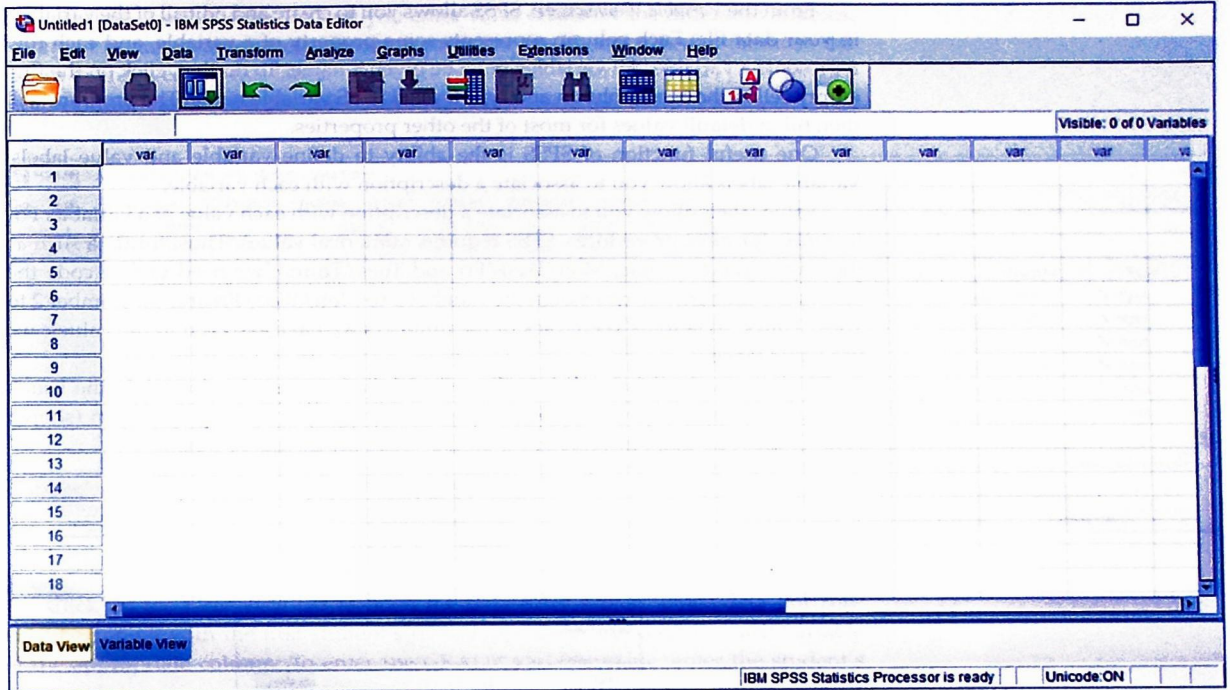
In the SPSS data window, columns represent variables, and rows represent participants. Therefore, we will be creating a data file with six columns (variables) and two rows (students/participants).

Section 1.3 Defining Variables

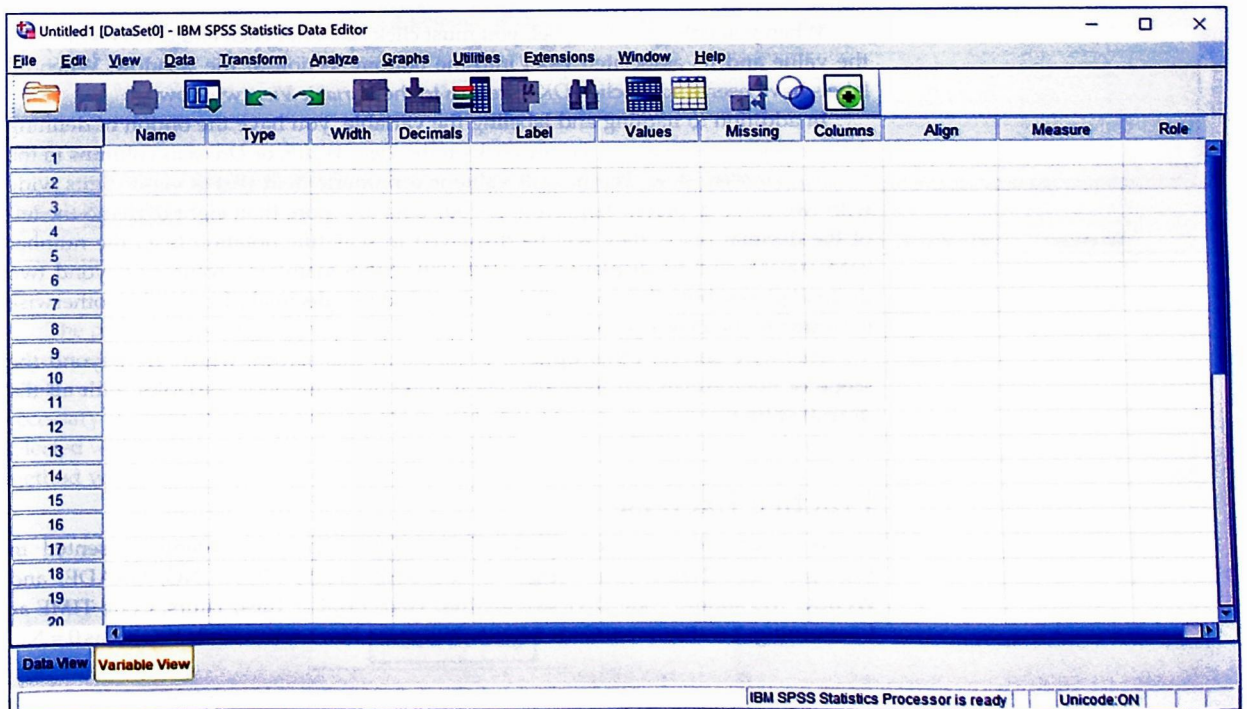
Before we can enter any data, we must first enter some basic information about each variable into SPSS. For instance, variables must first be given names that

- begin with a letter, and
- do not contain a space.

Thus, the variable name “Q7” is acceptable, while the variable name “7Q” is not. Similarly, the variable name “PRE_TEST” is acceptable, but the variable name “PRE TEST” is not. Capitalization does not matter, but variable names are capitalized in this text to make it clear when we are referring to a variable name, even if the variable name is not necessarily capitalized in screenshots.



To define a variable, click on the *Variable View* tab at the bottom of the main screen. This will show you the *Variable View* window. To return to the *Data View* window, click on the *Data View* tab.

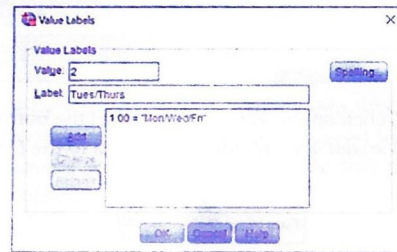
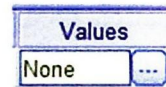


From the *Variable View* screen, SPSS allows you to create and edit all of the variables in your data file. Each column represents some property of a variable, and each row represents a variable. All variables must be given a name. To do that, click on the first empty cell in the *Name* column and type a valid SPSS variable name. The program will then fill in default values for most of the other properties.

One useful function of SPSS is the ability to define variable and value labels. Variable labels allow you to associate a description with each variable.

Value labels allow you to associate a description with each value of a variable. For instance, for most procedures, SPSS requires numerical values. Thus, for data such as the day of the class (i.e., Mon/Wed/Fri and Tues/Thurs), we need to first code the values as numbers. We can assign the number 1 to Mon/Wed/Fri and the number 2 to Tues/Thurs. To help us keep track of the numbers we have assigned to the values, we use value labels.

To assign value labels, click in the cell you want to assign values to in the *Values* column (in this case, for Variable 2). This will bring up a small gray button (shown below). Click on that button to bring up the Value Labels dialog box.



When you enter a value label, you must click *Add* after each entry. This will move the value and its associated label into the bottom section of the window. When all labels have been added, click *OK* to return to the *Variable View* window.

In addition to naming and labeling the variable, you have the option of defining the variable type. To do so, simply click on the *Type*, *Width*, or *Decimals* columns in the *Variable View* window. The default value is a numeric field that is eight digits wide with two decimal places displayed. If your data are more than eight digits to the left of the decimal place, they will be displayed in scientific notation (e.g., the number 2,000,000,000 will be displayed as 2.00E+09).² SPSS maintains accuracy beyond two decimal places, but all output will be rounded to two decimal places unless otherwise indicated in the *Decimals* column.

There are several other options available in this screen, which are beyond the scope of this text. In our example, we will be using numeric variables with all the default values.

Practice Exercise

Create a data file for the six variables and two sample students presented in Example 1.2.1. Name your variables: ID, DAY, TIME, MORNING, GRADE, and WORK. You should code DAY as 1 = Mon/Wed/Fri, 2 = Tues/Thurs. Code TIME as 1 = morning, 2 = afternoon. Code MORNING as 0 = No, 1 = Yes. Code WORK as 0 = No,

1 = Part-time, 2 = Full-time. Be sure you enter value labels for the different variables. Note that because value labels are not appropriate for ID and GRADE (because the values themselves serve as labels), these are not coded. When complete, your *Variable* window should look like the screenshot below.

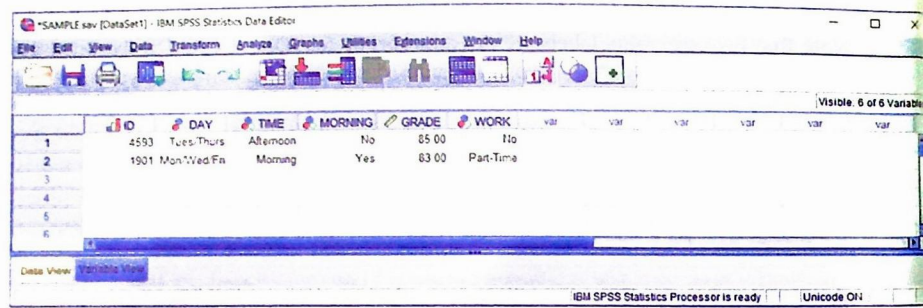
	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	ID	Numeric	8	0		None	None	8	Right	Ordinal	Input
2	DAY	Numeric	8	2		{1,00, Mon/...	None	8	Right	Nominal	Input
3	TIME	Numeric	8	2	What is the tim...	{1,00, Morni...	None	8	Right	Nominal	Input
4	MORNING	Numeric	8	2	Are you a morn...	{,00, No}...	None	9	Right	Nominal	Input
5	GRADE	Numeric	8	2		None	None	8	Right	Scale	Input
6	WORK	Numeric	8	2		{,00, No}...	None	8	Right	Nominal	Input
7											

Click on the *Data View* tab to open the data-entry screen. Enter data horizontally, beginning with the first student's ID number. Enter the code for each variable in the appropriate column. To enter the GRADE variable value, enter the student's class grade.

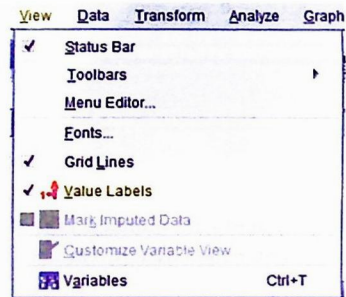
	ID	DAY	TIME	MORNING	GRADE	WORK	var	var	var	var	var	var
1	4593	2.00	2.00	.00	85.00	.00						
2	1901	1.00	1.00	1.00	83.00	1.00						
3												
4												
5												
6												

The previous *data* window can be changed to look like the screenshot on the next page by clicking on the *Value Labels* icon (see below). In this case, the cells display value labels rather than the corresponding codes. If data are entered in this mode, it is not necessary to enter codes, as clicking the button that appears in each cell as the cell is selected will present a drop-down list of the predefined labels. You may use whichever method you prefer.





Instead of clicking the *Value Labels* icon, you may toggle between views by clicking *Value Labels* under the *View* menu.



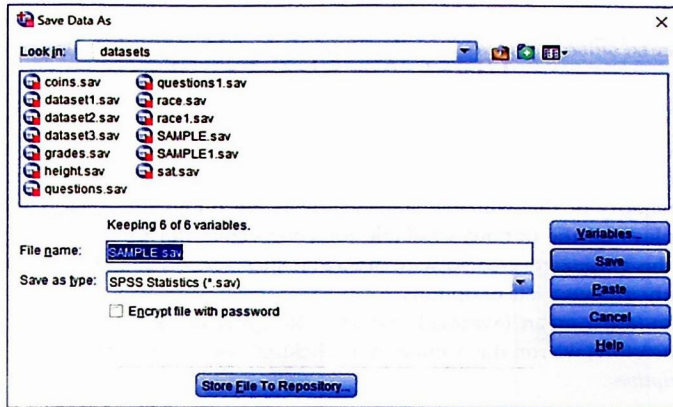
Section 1.4 Loading and Saving Data Files

Once you have entered your data, you will need to save it with a unique name so that you can retrieve it when necessary for later use.

Loading and saving SPSS data files works in the same way as most Windows-based software. Under the *File* menu, there are *Open*, *Save*, and *Save As* commands. SPSS data files have a ".sav" extension, which is added by default to the end of the filename (that is, do not type ".sav" after the filename; SPSS will add it automatically). This tells Windows that the file is an SPSS data file. Other SPSS extensions include ".spv" for saved output files and ".spss" for saved syntax files.

Save Your Data

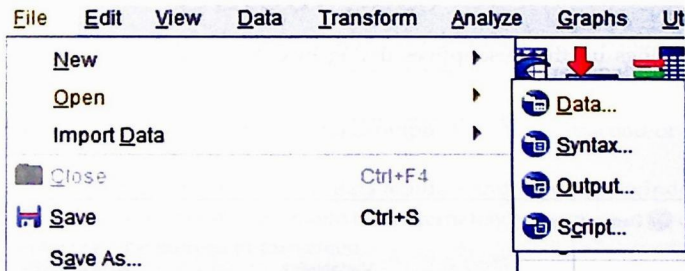




When you save your data file (by clicking *File*, then clicking *Save* or *Save As* to specify a unique name), pay special attention to where you save it. You will probably want to save your data on a removable USB drive so that you can take the file with you.

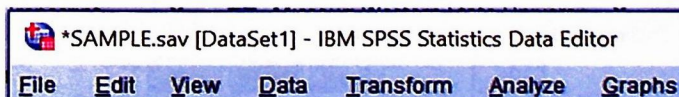
Load Your Data

When you load your data (by clicking *File*, then clicking *Open*, then *Data*, or by clicking the open file folder icon), you get a similar window. This window lists all files with the “.sav” extension. If you have trouble locating your saved file, make sure you are looking in the right directory.



Practice Exercise

To be sure that you have mastered saving and opening data files, name your sample data file “SAMPLE” and save it to a removable storage medium. Once it is saved, SPSS will display the name of the file at the top of the **data window**.



It is wise to save your work frequently, in case of computer crashes. Note that filenames may be uppercase or lowercase. In *this* text, uppercase is used for clarity. In naming files, though, screenshots may show lowercase only.

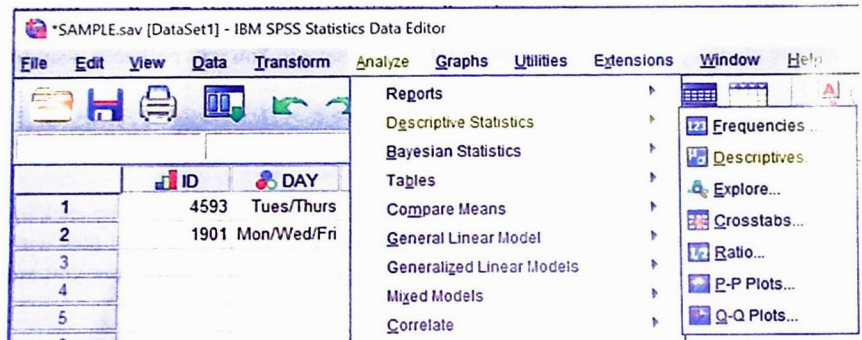
After you have saved your data, exit SPSS (by clicking *File*, then *Exit*). Restart SPSS and load your data by selecting the “SAMPLE.sav” file you just created.

Section 1.5 Running Your First Analysis

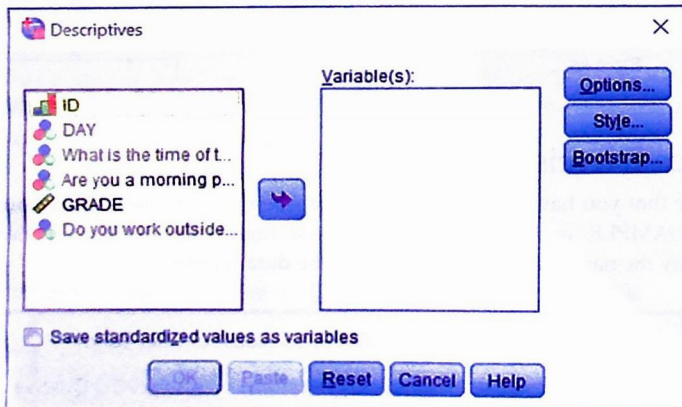
Any time you open a **data window**, you can run any of the analyses available. To get started, we will calculate the students' average grade. (With only two students, you can easily check your answer by hand, but imagine a data file with 10,000 student records.)

The majority of the available statistical tests are under the *Analyze* menu. This menu displays all the options available for your version of the SPSS program (the menus in this book were created with SPSS Statistics Version 26). Other versions may have slightly different sets of options.

To calculate a **mean** (average), we are asking the computer to summarize our dataset. Therefore, we run the command by clicking *Analyze*, then *Descriptive Statistics*, then *Descriptives*.

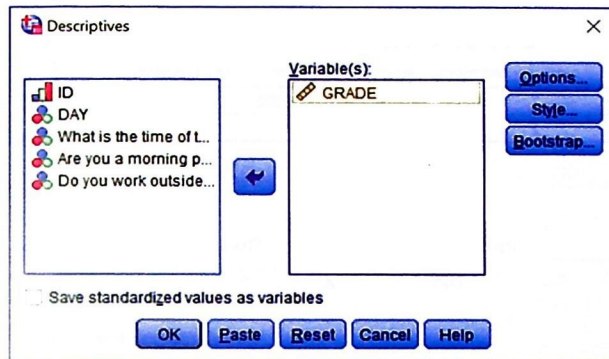


This brings up the Descriptives dialog box. Note that the left side of the box contains a list of all the variables in our data file. On the right is an area labeled *Variable(s)*, where we can specify the variables we would like to use in this particular analysis.



We want to compute the **mean** for the variable called GRADE. Thus, we need to select the variable name in the left window (by clicking on it). To transfer it to the right window, click on the right arrow between the two windows. The arrow always points

to the window opposite the highlighted item and can be used to transfer selected variables in either direction. Note that double-clicking on the variable name will also transfer the variable to the opposite window. Standard Windows conventions of “Shift” clicking or “Ctrl” clicking to select multiple variables can be used as well. Note: Some configurations of SPSS show the variable names, and others show the variable labels (if any). This can be changed under *Edit* → *Options* → *General*.

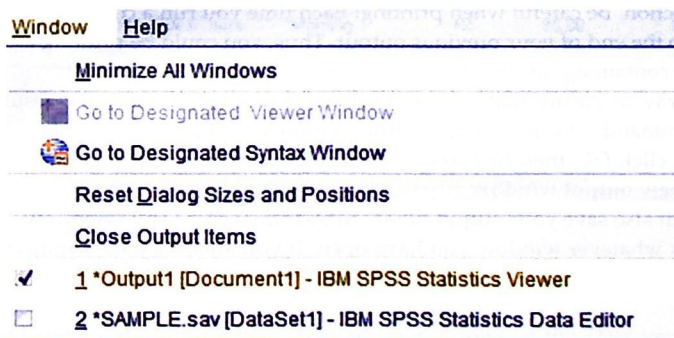


When we click on the *OK* button, the analysis will be conducted, and we will be ready to examine our output.

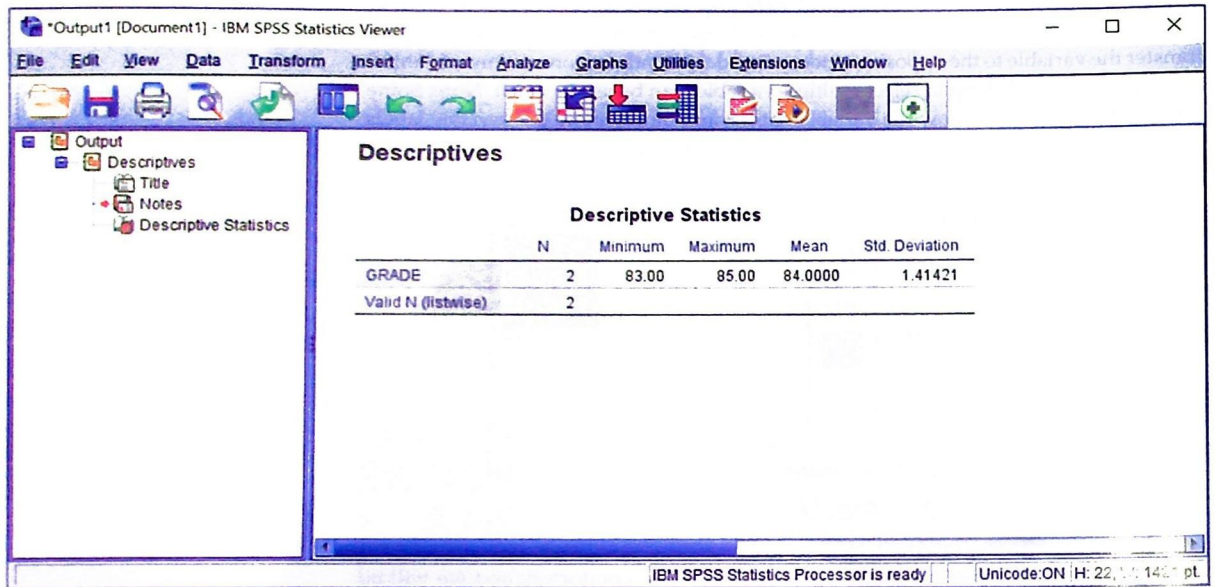
Section 1.6 Examining and Printing Output Files

After an analysis is performed, the output is placed in the **output window**, and the **output window** becomes the active window. If this is the first analysis you have conducted since starting SPSS, then a new **output window** will be created. If you have run previous analyses and saved them, your output is added to the end of your previous output.

To switch back and forth between the **data window** and the **output window**, select the desired window from the *Window* menu bar. Alternately, you can select the window using the taskbar at the bottom of the screen.



The **output window** is split into two sections. The left section is an outline of the output (SPSS refers to this as the *outline view*). The right section is the output itself.



The section on the left of the **output window** provides an outline of the entire **output window**. All of the analyses are listed in the order in which they were conducted. Note that this outline can be used to quickly locate a section of the output. Simply click on the section you would like to see, and the right window will jump to the appropriate place.

Clicking on a statistical procedure also selects all of the output for that command. By pressing the *Delete* key, that output can be deleted from the **output window**. This is a quick way to be sure that the **output window** contains only the desired output. Output can also be selected and pasted into a word processor or spreadsheet by clicking *Edit*, then *Copy* to copy the output. You can then switch to your word processor and click *Edit*, then *Paste*.

To print your output, simply click *File*, then *Print*, or click on the printer icon on the toolbar. You will have the option of printing all of your output or just the currently selected section. Be careful when printing! Each time you run a command, the output is added to the end of your previous output. Thus, you could be printing a very large output file containing information you may not want or need.

One way to ensure that your **output window** contains only the results of the **current command** is to create a new **output window** just before running the command. To do this, click *File*, then *New*, then *Output*. All your subsequent commands will go into your new **output window**.

You can also save your output files as SPSS format files (.spv extension). Note that SPSS saves whatever window you have open. If you are on a **data window** you will save your data. If you are on an **output window** it will save your output.

Practice Exercise

Load the sample data file you created earlier (SAMPLE.sav). Run the *Descriptives* command for the variable GRADE, and print the output. Next, select the **data window** and print it.

Section 1.7 Modifying Data Files

Once you have created a data file, it is really quite simple to add additional cases (rows/participants) or additional variables (columns). Consider Example 1.7.1.

Example 1.7.1 Two more students provide you with surveys. Their information is as follows:

Response Sheet 3

ID: 8734

Day of class: MWF X TTh

Class time: X Morning Afternoon

Are you a morning person? Yes X No

Final grade in class: 80%

Do you work outside school? Full-time Part-time

 X No

Response Sheet 4

ID: 1909

Day of class: X MWF TTh

Class time: X Morning Afternoon

Are you a morning person? X Yes No

Final grade in class: 73%

Do you work outside school? Full-time X Part-time

 No

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

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

5: ID Visible: 6 of 6 Variables

	ID	DAY	TIME	MORNING	GRADE	WORK	var	var	var	var
1	4593	Tues/Thurs	Afternoon	No	85.00	No				
2	1901	Mon/Wed/Fri	Morning	Yes	83.00	Part-Time				
3	8734	Tues/Thurs	Morning	No	80.00	No				
4	1909	Mon/Wed/Fri	Morning	Yes	73.00	Part-Time				
5										
6										
7										
8										

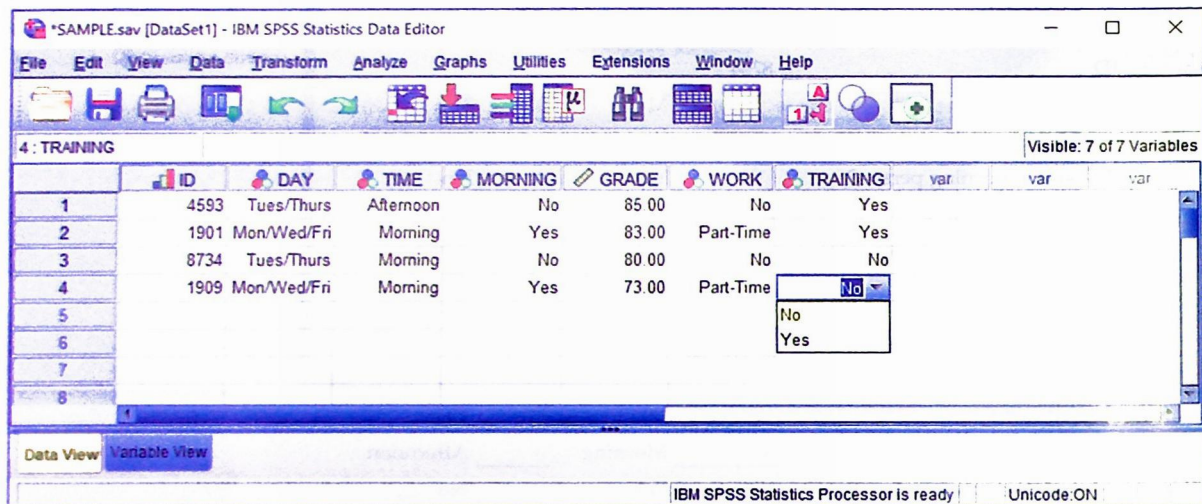
Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

To add these data, simply place two additional rows in the *Data View* window (after loading your sample data). Notice that as new participants are added, the row numbers become bold. When done, the screen should look like the screenshot above.

New variables can also be added. For example, if the first two participants were given special training on time management, and the two new participants were not, the data file can be changed to reflect this additional information. The new variable

could be called TRAINING (whether or not the participant received training), and it would be coded so that 0 = No and 1 = Yes. Thus, the first two participants would be assigned a "1" and the last two participants a "0." To do this, switch to the *Variable View* window, then add the TRAINING variable to the bottom of the list. Then switch back to the *Data View* window to update the data.



Adding data and variables are logical extensions of the procedures we used to originally create the data file. Save this new data file. We will be using it again later in this book.

Practice Exercise

Follow the previous example (where TRAINING is the new variable). Make the modifications to your SAMPLE.sav data file and save it.

Chapter 2

Entering and Modifying Data

In Chapter 1, we learned how to create and save a simple data file, perform a basic analysis, and examine the output. In this section, we will go into more detail about variables and data.

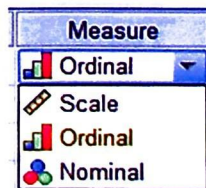
Section 2.1 Variables and Data Representation

In SPSS, variables are represented as columns in the data file. Participants are represented as rows. Thus, if we collect four pieces of information from 100 participants, we will have a data file with four columns and 100 rows.

Measurement Scales

There are four types of measurement scales: **nominal**, **ordinal**, **interval**, and **ratio**. While the measurement scale will determine which statistical technique is appropriate for a given set of data, SPSS generally does not discriminate. Thus, we start this section with this warning: If you ask it to, SPSS may conduct an analysis that is not appropriate for your data. For a more complete description of these four measurement scales, consult your statistics text or the Glossary in Appendix E.

Newer versions of SPSS allow you to indicate which types of data you have when you define your variable. You do this using the *Measure* column. You can indicate *Scale*, *Ordinal*, or *Nominal* (SPSS does not distinguish between **interval** and **ratio** scales).



Look at the SAMPLE.sav data file we created in Chapter 1. We calculated a **mean** for the variable GRADE. GRADE was measured on a **ratio scale**, and the **mean** is an acceptable summary statistic (assuming that the distribution is **normal**).

We could have had SPSS calculate a **mean** for the variable TIME instead of GRADE. If we did, we would get the output presented on the next page.

The screenshot shows the IBM SPSS Statistics Viewer interface. The main window displays the 'Descriptives' output for the variable 'What is the time of the class?'. The 'Descriptive Statistics' table is as follows:

	N	Minimum	Maximum	Mean	Std. Deviation
What is the time of the class?	4	1.00	2.00	1.2500	.50000
Valid N (listwise)	4				

The status bar at the bottom indicates 'IBM SPSS Statistics Processor is ready' and 'Unicode: ON | H: 22, W: 164 pt'.

The output indicates that the average TIME was 1.25. Remember that TIME was coded as an ordinal variable (1 = morning class, 2 = afternoon class). Though the mean is not an appropriate statistic for an **ordinal scale**, SPSS calculated it anyway. The importance of considering the type of data cannot be overemphasized. Just because SPSS will compute a statistic for you does not mean that you should use it. Later in the text, when specific statistical procedures are discussed, the conditions under which they are appropriate will be addressed. Please note that there are some procedures (e.g., graphs and nonparametric tests) where SPSS limits what you can do based on the measurement scale. However, more often than not, it is up to the user to make that decision.

Missing Data

Often, participants do not provide complete data. For example, for some students, you may have a pretest score but not a posttest score. Perhaps one student left one question blank on a survey, or perhaps she did not state her age. Missing data can weaken any analysis. Often, a single missing answer can eliminate a subject from all analyses.

	q1	q2	total
1	2.00	2.00	4.00
2	3.00	1.00	4.00
3	4.00	3.00	7.00
4	2.00		
5	1.00	2.00	3.00

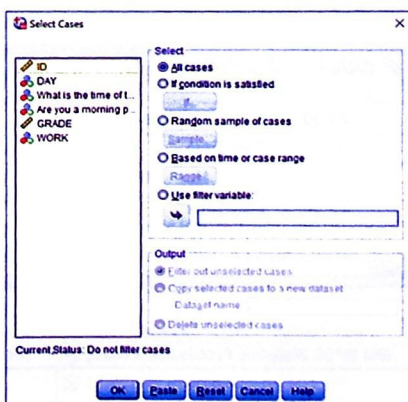
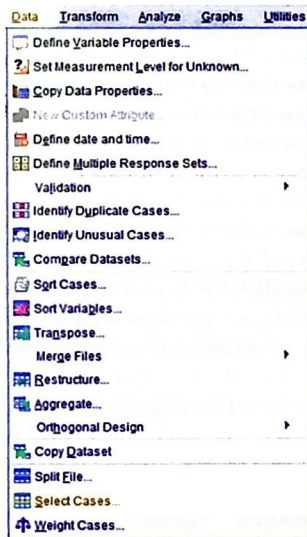
If you have missing data in your dataset, leave that cell blank. In the example shown above, the fourth subject did not complete Question 2 (q2). Note that the total score (which is calculated from both questions) is also blank because of the missing data for Question 2. SPSS represents missing data in the **data window** with a period (although you should not enter a period—just leave it blank). It is NOT good practice to create a filler value (e.g., “999” or “0”) to represent blank scores, because SPSS will see it as a value with meaning, whereas it will treat truly blank values as missing.

Section 2.2 Selection and Transformation of Data

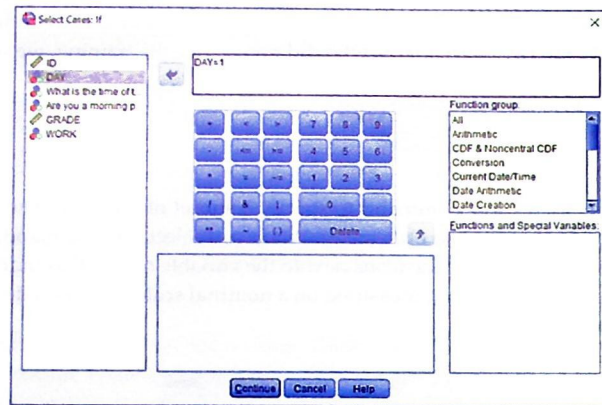
We often have more data in a data file than we want to include in a specific analysis. For instance, our sample data file contains data from four participants, two of whom received special training and two of whom did not. If we wanted to conduct an analysis using only the two participants who did not receive the training, we would need to specify the appropriate subset.

Selecting a Subset

We can use the *Select Cases* command to specify a subset of our data. The *Select Cases* command is located under the *Data* menu. When you select this command, the dialog box below will appear. (Note the icons next to the variable names that indicate that all variables were defined as being measured on a **nominal** scale except grade, which was defined as **scale**.)



You can specify which cases (participants) you want to select by using the selection criteria, which appear on the right side of the Select Cases dialog box. By default, *All cases* will be selected. The most common way to select a subset is to click *If condition is satisfied*, then click on the button labeled *If*. This will bring up a new dialog box that allows you to indicate which cases you would like to use.



You can enter the logic used to select the subset in the upper section. If the logical statement is true for a given case, then that case will be selected. If the logical statement is false that case will not be selected. For instance, you can select all cases that were coded as Mon/Wed/Fri by entering the formula $DAY = 1$ in the upper-left part of the window. If DAY is 1, then the statement will be true, and SPSS will select the case. If DAY is anything other than 1, the statement will be false, and the case will not be selected. Once you have entered the logical statement, click *Continue* to return to the Select Cases dialog box. Then, click *OK* to return to the data window.

After you have selected the cases, the data window will slightly change. The cases that were not selected will be marked with a diagonal line through the case number. For instance, for our sample data, the first and third cases are not selected. Only the second and fourth cases are selected for this subset.

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

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

8 : TIME Visible: 7 of 7 Variables

	ID	DAY	TIME	MORNIN G	GRADE	WORK	filter_\$	var	var
1	4593 00	Tues/Thur	Afternoon	No	85 00	No	Not Selected		
2	1901 00	Mon/Wed/Fri	Morning	Yes	83 00	Part-Time	Selected		
3	8734 00	Tues/Thur	Morning	No	80 00	No	Not Selected		
4	1909 00	Mon/Wed/Fri	Morning	Yes	73 00	Part-Time	Selected		
5									

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON Filter On

An additional variable will also be created in your data file. The new variable is called $FILTER_S$ and indicates whether a case was selected or not.

If we calculate a mean GRADE using the subset we just selected, we will receive the output here. Notice that we now have a mean of 78.00 with a sample size (*N*) of 2 instead of 4.

Descriptive Statistics

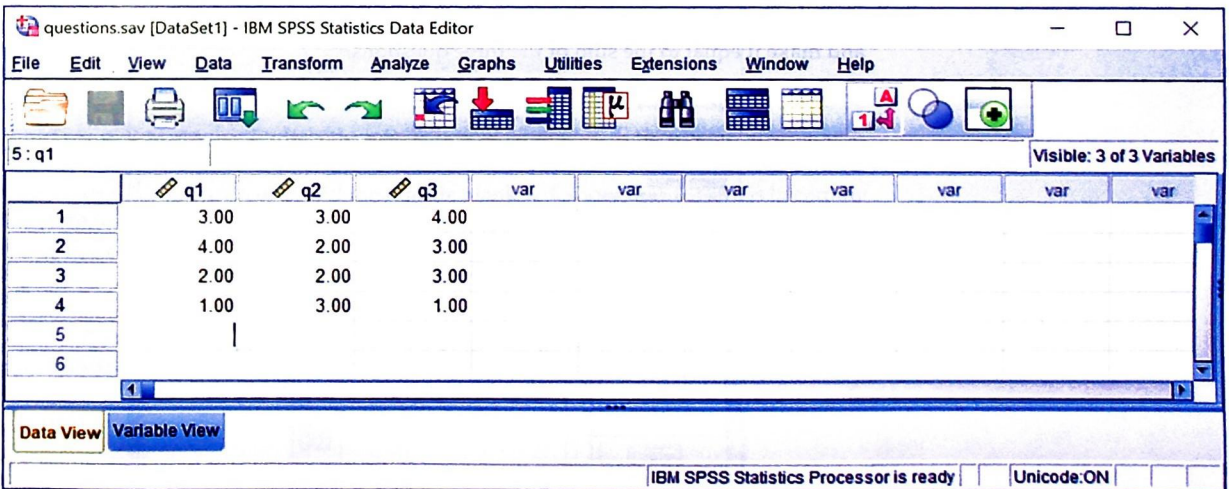
	N	Minimum	Maximum	Mean	Std. Deviation
GRADE	2	73.00	83.00	78.0000	7.07107
Valid N (listwise)	2				

Be careful when you select subsets. *The subset remains in effect until you run the command again and select all cases.* You can tell if you have a subset selected because the bottom of the **data window** will indicate that a filter is on. In addition, when you examine your output, *N* will be less than the total number of records in your dataset if a subset is selected. The diagonal lines through some cases will also be evident when a subset is selected. Be careful not to save your data file with a subset selected, as this can cause considerable confusion later.

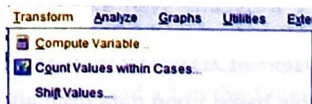
Computing a New Variable

SPSS can also be used to compute a new variable or manipulate your existing variables. To illustrate this, we will create a new data file. This file will contain data for four participants and three variables (Q1, Q2, and Q3). The variables represent the number of points each participant received on three different questions. Now enter the data shown on the screen below. When done, save this data file as "QUESTIONS.sav." We will be using it again in later chapters.

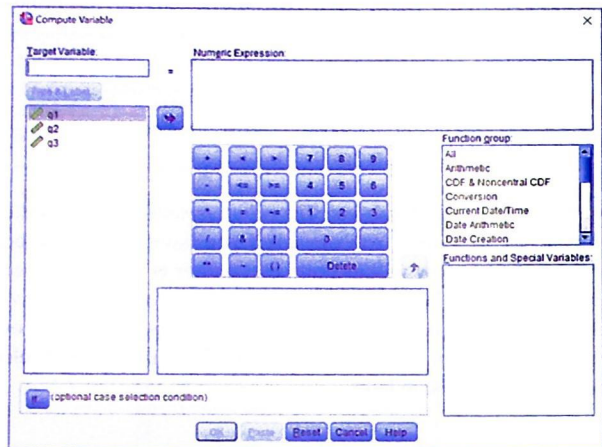
62983



Now you will calculate the total score for each subject. We could do this manually, but if the data file were large, or if there were a lot of questions, this would take a long time. It is more efficient (and more accurate) to have SPSS compute the totals for you. To do this, click *Transform*, and then click *Compute Variable*.

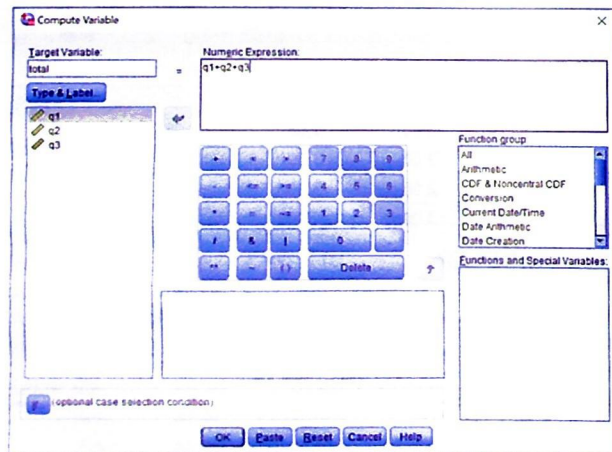


After clicking the *Compute Variable* command, we get the dialog box shown below.



The blank field marked *Target Variable* is where we enter the name of the new variable we want to create. In this example, we are creating a variable called *TOTAL*, so type the word *total*.

Notice that there is an equals sign between the *Target Variable* blank and the *Numeric Expression* blank. These two blank areas are the two sides of an equation that SPSS will calculate. For instance, $total = Q1 + Q2 + Q3$ is the equation that is entered in the sample presented here (screenshot shown above). Note that it is possible to create any equation here simply by using the number and operational keypad at the bottom of the dialog box. When we click *OK*, SPSS will create a new variable called *TOTAL* and make it equal to the sum of the three questions.

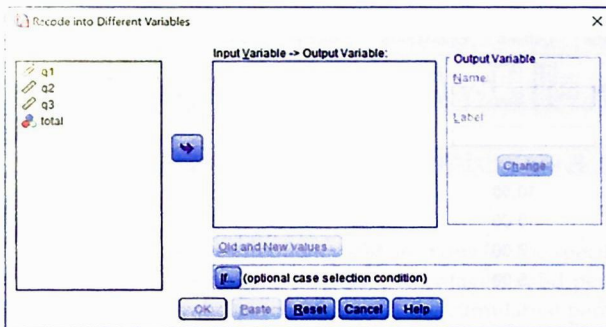
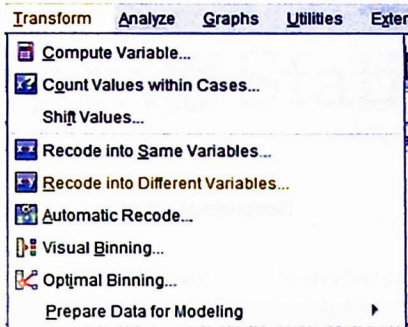


Save your data file again so that the new variable will be available for future sessions.

Recoding a Variable—Different Variable

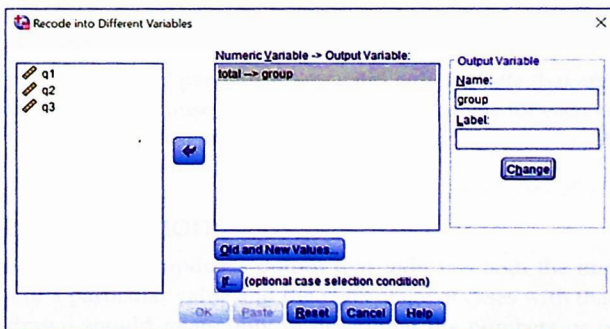
SPSS can create a new variable based upon data from another variable. Say we want to split our participants on the basis of their total score. We want to create a variable

called **GROUP**, which is coded 1 if the total score is low (less than or equal to 8) or 2 if the total score is high (9 or larger). To do this, we click *Transform*, then *Recode into Different Variables*.

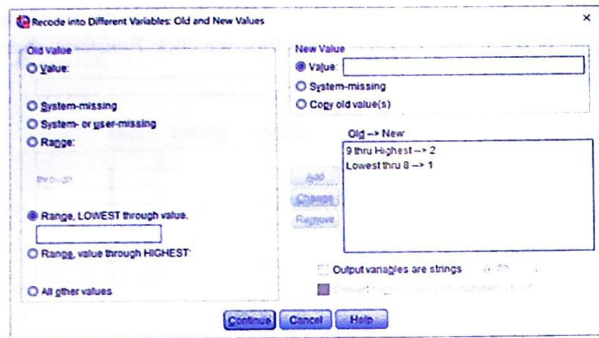


This will bring up the **Recode into Different Variables dialog box** shown above. Transfer the variable **TOTAL** to the middle blank. Type *group* in the *Name* field under *Output Variable*. Click *Change*, and the middle blank will show that **TOTAL** is becoming **GROUP**, as shown below.

Click *Old and New Values*. This will bring up the **Recode dialog box** below.



In the example shown here, we have entered a 9 in the *Range, value through HIGHEST* field, and a 2 in the *Value* field under *New Value*. When we click *Add*, the blank on the right displays the recoding formula. We next entered an 8 on the left in the *Range, LOWEST through value* blank, and a 1 in the *Value* field under *New Value*. Click *Add*, then *Continue*.



Click OK. You will be redirected to the data window shown below. A new variable (GROUP) will have been added and coded as 1 or 2, based on TOTAL.

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

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

5: q1 Visible: 5 of 5 Variables

	q1	q2	q3	total	group	var	var	var	var
1	3 00	3 00	4 00	10 00	2 00				
2	4 00	2 00	3 00	9 00	2 00				
3	2 00	2 00	3 00	7 00	1 00				
4	1 00	3 00	1 00	5 00	1 00				
5									
6									

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

Chapter 3

Descriptive Statistics

In Chapter 2, we discussed many of the options available in SPSS for dealing with data. Now we will discuss ways to summarize our data. The procedures used to describe and summarize data are called **descriptive statistics**.

Section 3.1 Frequency Distributions and Percentile Ranks for a Single Variable

Description

The *Frequencies* command produces frequency distributions for the specified variables. The output includes the number of occurrences, percentages, valid percentages, and cumulative percentages. The valid percentages and the cumulative percentages comprise only the data that are not designated as missing.

The *Frequencies* command is useful for describing samples where the **mean** is not useful (e.g., **nominal** or **ordinal** scales). It is also useful as a method of getting the feel for your data. It provides more information than just a **mean** and **standard deviation** and can be useful in determining **skew** and identifying **outliers**. A special feature of the command is its ability to determine **percentile ranks**.

Assumptions

Cumulative percentages and **percentiles** are valid only for data that are measured on at least an **ordinal scale**. Because the output contains one line for each value of a variable, this command works best on variables with a relatively small number of values.

Drawing Conclusions

The *Frequencies* command produces output that indicates both the number of cases in the sample of a particular value and the percentage of cases with that value. Thus, conclusions drawn should relate only to describing the numbers or percentages of cases in the sample. If the data are at least ordinal in nature, conclusions regarding the cumulative percentage and/or **percentiles** can be drawn.

SPSS Data Format

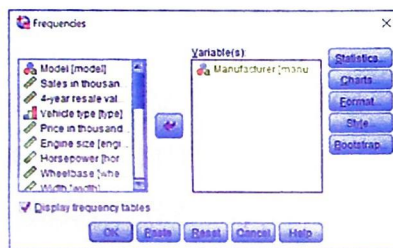
The SPSS data file for obtaining frequency distributions requires only one variable, and that variable can be of any type.

Creating a Frequency Distribution

This example uses the CAR_SALES.sav data file that comes with SPSS. If you are using SPSS Version 26, it will be located at

C:\Program Files\IBM\SPSS\Statistics\26\Samples\English\car_sales.sav

To run the *Frequencies* command, click *Analyze*, then *Descriptive Statistics*, then *Frequencies*. This will bring up the main dialog box below. Transfer the variable for which you would like a frequency distribution into the *Variable(s)* blank shown to the right (MANUFACTURER in this case). Be sure that the *Display frequency tables* option is checked.



Note that the dialog boxes in SPSS show both the type of variable (the icon immediately to the left of the variable name) and the variable labels if they are entered. Thus, the variable MANUFACTURER shows up in the dialog box as *Manufacturer*.

Click *OK* to run the test.

Output for a Frequency Distribution

The output consists of two sections. The first section indicates the number of records with valid data for each variable selected. Records with a blank score are listed as missing. In this example, the data file contained 157 records.

The second section of the output contains a cumulative frequency distribution for each variable selected. At the top of the section, the variable label is given. The output itself consists of five columns. The first column lists the values of the variable sorted in alphabetical order. There is a row for each value of your variable, and additional rows are added at the bottom for the Total and Missing data. The second column gives the frequency of each value, including missing values. The third column gives the percentage of all records (including records with missing data) for each value. The fourth column, labeled *Valid Percent*, gives the percentage of records (without including records with missing data) for each value. If there were any missing values, these values would be larger than the values in column three because the total number of records would have been reduced by the number of records with missing values. The final column gives cumulative percentages. Cumulative percentages indicate the percentage of records with a score equal to or smaller than the current value. Thus, the last value is always 100 percent. These values are equivalent to percentile ranks for

the values listed. Note: SPSS will provide cumulative percentages even for nominal variables and other variables where it does not make sense. For example, the variable MANUFACTURER is nominal.

Statistics

Manufacturer

N Valid 157

Missing 0

Manufacturer

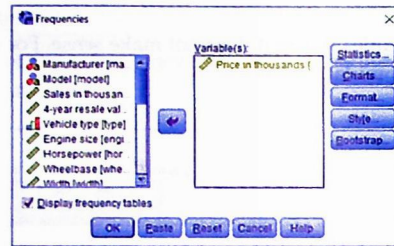
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Acura	4	2.5	2.5	2.5
	Audi	3	1.9	1.9	4.5
	BMW	3	1.9	1.9	6.4
	Buick	4	2.5	2.5	8.9
	Cadillac	5	3.2	3.2	12.1
	Chevrolet	9	5.7	5.7	17.8
	Chrysler	7	4.5	4.5	22.3
	Dodge	11	7.0	7.0	29.3
	Ford	11	7.0	7.0	36.3
	Honda	5	3.2	3.2	39.5
	Hyundai	3	1.9	1.9	41.4
	Infiniti	1	.6	.6	42.0
	Jaguar	1	.6	.6	42.7
	Jeep	3	1.9	1.9	44.6
	Lexus	6	3.8	3.8	48.4
	Lincoln	3	1.9	1.9	50.3
	Mercedes-Benz	9	5.7	5.7	56.1
	Mercury	6	3.8	3.8	59.9
	Mitsubishi	7	4.5	4.5	64.3
	Nissan	7	4.5	4.5	68.8
	Oldsmobile	6	3.8	3.8	72.6
	Plymouth	4	2.5	2.5	75.2
	Pontiac	6	3.8	3.8	79.0
	Porsche	3	1.9	1.9	80.9
	Saab	2	1.3	1.3	82.2
	Saturn	5	3.2	3.2	85.4
	Subaru	2	1.3	1.3	86.6
	Toyota	9	5.7	5.7	92.4
	Volkswagen	6	3.8	3.8	96.2
	Volvo	6	3.8	3.8	100.0
	Total	157	100.0	100.0	

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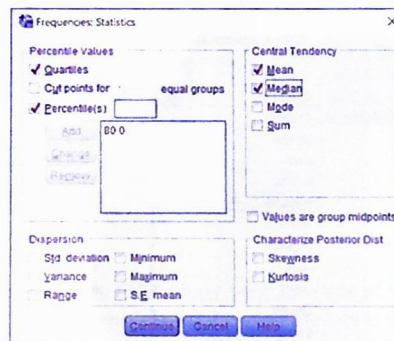
Determining Percentile Ranks

The *Frequencies* command can be used to provide a number of **descriptive statistics**, as well as a variety of percentile values (including **quartiles**, cut points, and scores corresponding to a specific **percentile rank**). Let us look at statistics for the variable PRICE.

To obtain either the descriptive or percentile functions of the *Frequencies* command, click the *Statistics* button at the top right of the main dialog box.



This brings up the Frequencies: Statistics dialog box below. Note that the *Central Tendency* and *Dispersion* sections of this box are useful for calculating values, such as the **median** or **mode**, that cannot be calculated with the *Descriptives* command (see Section 3.3). Check any additional desired statistic by clicking on the blank next to it. (In our example here, let us determine the quartiles, 80th percentile, mean, and median.)



For percentiles, enter the desired percentile rank in the blank to the right of the *Percentile(s)* label. Then, click *Add* to add it to the list of percentiles requested. Once you have selected all your required statistics, click *Continue* to return to the main dialog box. Click *OK*.

Output for Percentile Ranks

Statistics		
Price in thousands		
N	Valid	155
	Missing	2
Mean		27.39075
Median		22.79900
Percentiles	25	17.89000
	50	22.79900
	75	31.96500
	80	36.21020

The **Statistics** dialog box adds on to the first section of output from the *Frequencies* command. The output contains a row for each piece of information you requested. In

the previous example, we checked *Quartiles* and asked for the 80th percentile. Thus, the output contains rows for the 25th, 50th, 75th, and 80th percentiles.

Practice Exercise

Using Practice Dataset 1 in Appendix B, create a frequency distribution table for the mathematics skills scores. Determine the mathematics skills score at which the 60th percentile lies.

Section 3.2 Frequency Distributions and Percentile Ranks for Multiple Variables

Description

The *Crosstabs* command produces frequency distributions for multiple variables. The output includes the number of occurrences of each combination of **levels** of each variable. It is possible to have the command give percentages for any or all variables.

The *Crosstabs* command is useful for describing samples where the **mean** is not useful (e.g., **nominal** or **ordinal** scales). It is also useful as a method for getting a feel for your data.

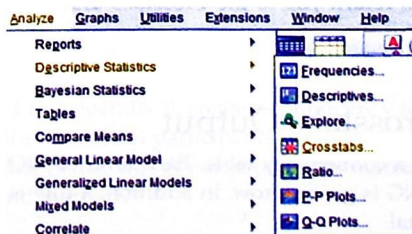
Assumptions

Because the output contains a row or column for each value of a variable, this command works best on variables with a relatively small number of values.

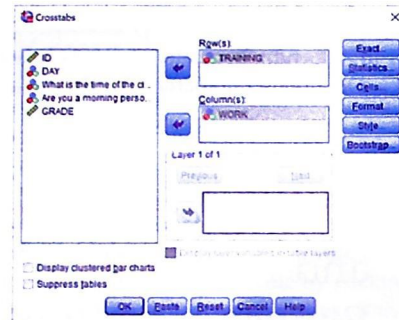
SPSS Data Format

The SPSS data file for the *Crosstabs* command requires two or more variables. Those variables can be of any type.

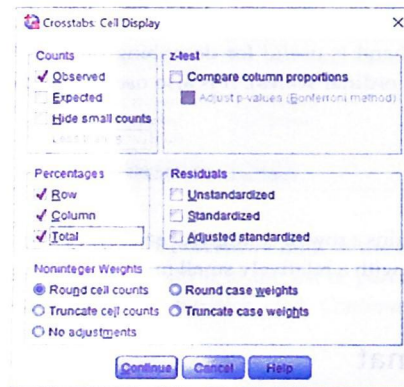
Running the Command



This example uses the `SAMPLE.sav` data file, which you created in Chapter 1. To run the procedure, click *Analyze*, then *Descriptive Statistics*, then *Crosstabs*. This will bring up the main Crosstabs dialog box, which is shown below.



The dialog box initially lists all variables on the left and contains two blank boxes labeled *Row(s)* and *Column(s)*. Enter one variable (`TRAINING`) in the *Row(s)* box. Enter the second (`WORK`) in the *Column(s)* box. To analyze more than two variables, you would enter the third, fourth, and so on, in the unlabeled area (just under the *Layer* indicator).



The *Cells* button allows you to specify percentages and other information to be generated for each combination of values. Click *Cells*, and you will get the box shown above, with *Observed* and *Round cell counts* selected by default.

For the example presented here, check *Row*, *Column*, and *Total* percentages. Then click *Continue*. This will return you to the Crosstabs dialog box. Click *OK* to run the analysis.

Interpreting Crosstabs Output

The output consists of a contingency table. Each level of `WORK` is given a column. Each level of `TRAINING` is given a row. In addition, a row is added for total, and a column is added for total.

Crosstabs

Case Processing Summary

	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
TRAINING * WORK	4	100.0%	0	0.0%	4	100.0%

TRAINING * WORK Crosstabulation

		Count	WORK		Total
			No	Part-Time	
TRAINING	No	1	1	2	
	% within TRAINING	50.0%	50.0%	100.0%	
	% within WORK	50.0%	50.0%	50.0%	
	% of Total	25.0%	25.0%	50.0%	
Yes	Count	1	1	2	
	% within TRAINING	50.0%	50.0%	100.0%	
	% within WORK	50.0%	50.0%	50.0%	
	% of Total	25.0%	25.0%	50.0%	
Total	Count	2	2	4	
	% within TRAINING	50.0%	50.0%	100.0%	
	% within WORK	100.0%	100.0%	100.0%	
	% of Total	50.0%	50.0%	100.0%	

Each cell contains the number of participants (for example, one participant received no training and does not work; two participants received no training, regardless of employment status).

The percentages for each cell are also shown. Row percentages add up to 100 percent horizontally. Column percentages add up to 100 percent vertically. For instance, of all the individuals who had no training, 50 percent did not work and 50 percent worked part-time (using the “% within TRAINING” row). Of the individuals who did not work, 50 percent had no training and 50 percent had training (using the “% within WORK” row).

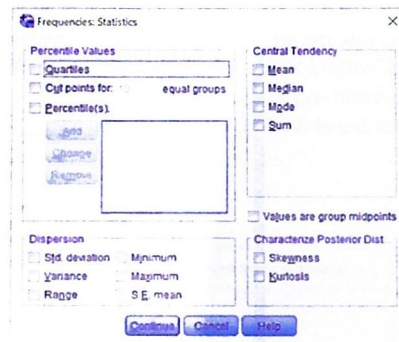
Practice Exercise

Using Practice Dataset 1 in Appendix B, create a contingency table using the *Crosstabs* command. Determine the number of participants in each combination of the variables SEX and MARITAL. What percentage of participants are married? What percentage of participants are male and married?

Section 3.3 Measures of Central Tendency and Measures of Dispersion for a Single Group

Description

Measures of central tendency are values that represent a typical member of the sample or population. The three primary types of measures are the **mean**, **median**, and **mode**. Measures of dispersion tell you the variability of your scores. The primary types are the **range** and the **standard deviation**. Together, a measure of central tendency and a measure of dispersion provide a great deal of information about the entire dataset.



We will discuss these measures of central tendency and measures of dispersion in the context of the *Descriptives* command. Note that many of these statistics can also be calculated with several other commands (e.g., the *Frequencies* or *Compare Means* commands are required to compute the **mode** or **median**—the *Statistics* option for the *Frequencies* command is shown above).

Assumptions

Each measure of central tendency and measure of dispersion has different assumptions associated with it. The **mean** is the most powerful measure of central tendency, and it has the most assumptions. For instance, to calculate a **mean**, the data must be measured on an **interval** or **ratio scale**. In addition, the distribution should be normally distributed or, at least, not highly skewed. The **median** requires at least **ordinal** data. Because the **median** indicates only the middle score (when scores are arranged in order), there are no assumptions about the shape of the distribution. The **mode** is the weakest measure of central tendency. There are no assumptions for the **mode**.

The **standard deviation** is the most powerful measure of dispersion, but it, too, has several requirements. It is a mathematical transformation of the **variance** (the **standard deviation** is the square root of the **variance**). Thus, if one is appropriate, the other is also appropriate. The **standard deviation** requires data measured on an **interval** or **ratio scale**. In addition, the distribution should be normal. The **range** is the weakest

measure of dispersion. To calculate a **range**, the variable must be at least **ordinal**. For **nominal scale** data, the entire frequency distribution should be presented as a measure of dispersion.

Drawing Conclusions

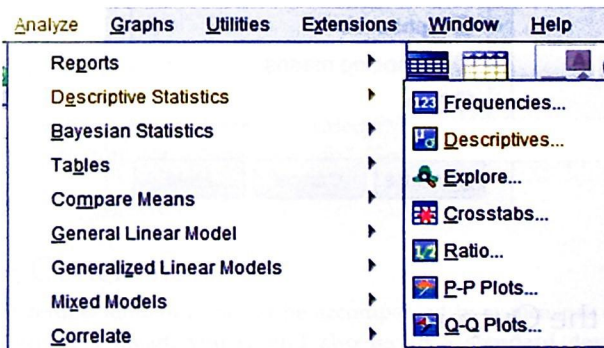
A measure of central tendency should be accompanied by a measure of dispersion. Thus, when reporting a **mean**, you should also report a **standard deviation**. When presenting a **median**, you should also state the **range** or **interquartile range**. The **interquartile range** can be determined using the *Frequencies* command.

SPSS Data Format

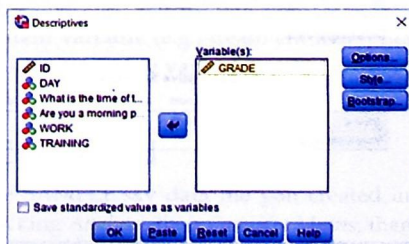
Only one variable is required.

Running the Command

The *Descriptives* command is the command you will most likely use for obtaining measures of central tendency and measures of dispersion. This example uses the *SAMPLE.sav* data file we used in the previous chapters.

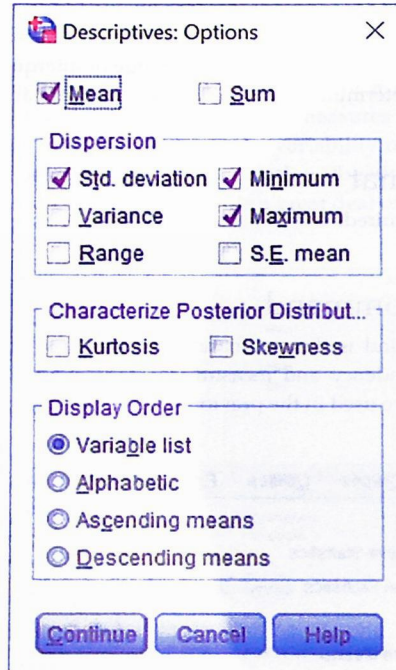


To run the command, click *Analyze*, then *Descriptive Statistics*, then *Descriptives*. This will bring up the main **dialog box** for the *Descriptives* command. Any variables you would like information about can be placed in the right blank by double-clicking them or by selecting them and then clicking on the arrow. Move the variable **GRADE** to the right for this example.



By default, you will receive the N (number of cases/participants), the minimum value, the maximum value, the mean, and the standard deviation. Note that some of these may not be appropriate for the types of data you have selected.

If you would like to change the default statistics that are given, click *Options* in the main dialog box. You will be given the Options dialog box shown below. Click *Continue* or *Cancel* to close the Options box. Then click *OK*.



Reading the Output

The output for the *Descriptives* command is quite straightforward. Each type of output requested is presented in a column, and each variable is given in a row. The output presented below is for the sample data file. It shows that we have one variable (GRADE) and that we obtained the N , minimum, maximum, mean, and standard deviation for this variable.

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
GRADE	4	73.00	85.00	80.2500	5.25198
Valid N (listwise)	4				

IBM SPSS Statistics Processor is ready | Unicode ON | H: 44, W: 634 pt.

Practice Exercise

Using Practice Dataset 1 in Appendix B, obtain the **descriptive statistics** for the age of the participants. What is the **mean**? The **median**? The **mode**? What is the **standard deviation**? Minimum? Maximum? The **range**? (Refer to Section 3.1 for assistance with **median** and **mode**.)

Section 3.4 Measures of Central Tendency and Measures of Dispersion for Multiple Groups

Description

The measures of central tendency discussed earlier are often needed not only for the entire dataset, but also for several subsets. One way to obtain these values for subsets is to use the data-selection techniques discussed in Chapter 2 and apply the *Descriptives* command to each subset. An easier way to perform this task is to use the *Means* command. The *Means* command is designed to provide **descriptive statistics** for subsets of your data.

Assumptions

The assumptions discussed in the section titled “Measures of Central Tendency and Measures of Dispersion for a Single Group” (Section 3.3) also apply to multiple groups.

Drawing Conclusions

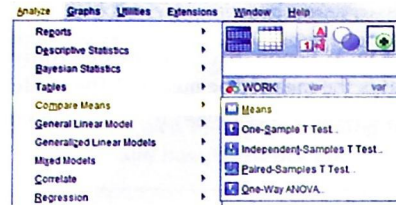
A measure of central tendency should be accompanied by a measure of dispersion. Thus, when giving a **mean**, you should also report a **standard deviation**. When presenting a **median**, you should also state the **range** or **interquartile range**.

SPSS Data Format

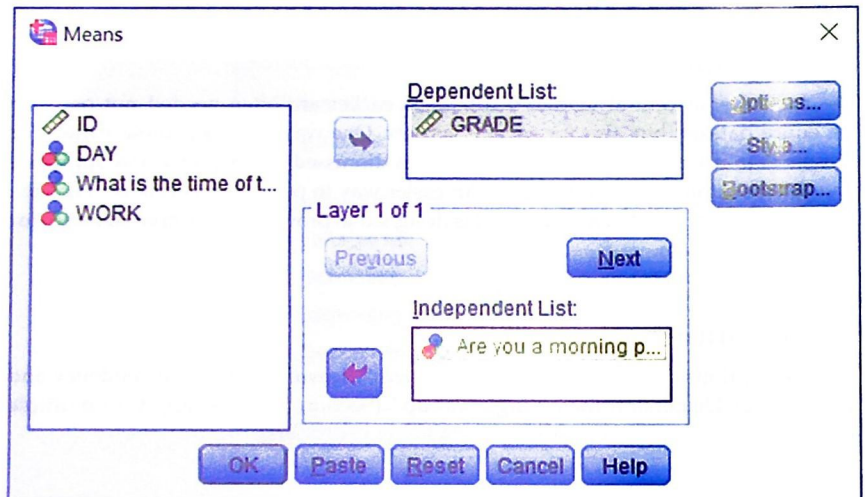
Two variables in the SPSS data file are required. One represents the **dependent variable** and will be the variable for which you receive the **descriptive statistics**. The other is the **independent variable** and will be used in creating the subsets. Note that while SPSS calls this variable an **independent variable**, it may not meet the strict criteria that define a true **independent variable** (e.g., treatment manipulation). Thus, some SPSS procedures refer to it as the **grouping variable**.

Running the Command

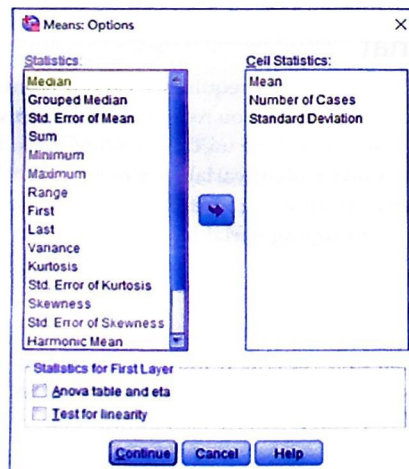
This example uses the *SAMPLE.sav* data file you created in Chapter 1. The *Means* command is run by clicking *Analyze*, then *Compare Means*, then *Means*.



This will bring up the main **dialog box** for the *Means* command. Place the selected variable in the blank field labeled *Dependent List*. Place the **grouping variable** in the box labeled *Independent List*. In this example, through use of the *SAMPLE.sav* data file, measures of central tendency and measures of dispersion for the variable *GRADE* will be given for each level of the variable *MORNING*.



By default, the mean, number of cases, and standard deviation are given. If you would like additional measures, click *Options* and you will be presented with the dialog box shown here. You can opt to include any number of measures.



Reading the Output

The output for the *Means* command is split into two sections. The first section, called a **case processing summary**, gives information about the data used. In our sample data file, there are four students (cases), all of whom were included in the analysis.

The screenshot shows the IBM SPSS Statistics Viewer window. The main area displays the output for the *Means* command. The output is organized into two sections: **Case Processing Summary** and **Report**.

Case Processing Summary

	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
GRADE * Are you a morning person?	4	100.0%	0	0.0%	4	100.0%

Report

Are you a morning person?	Mean	N	Std. Deviation
No	82.5000	2	3.53553
Yes	78.0000	2	7.07107
Total	80.2500	4	5.25198

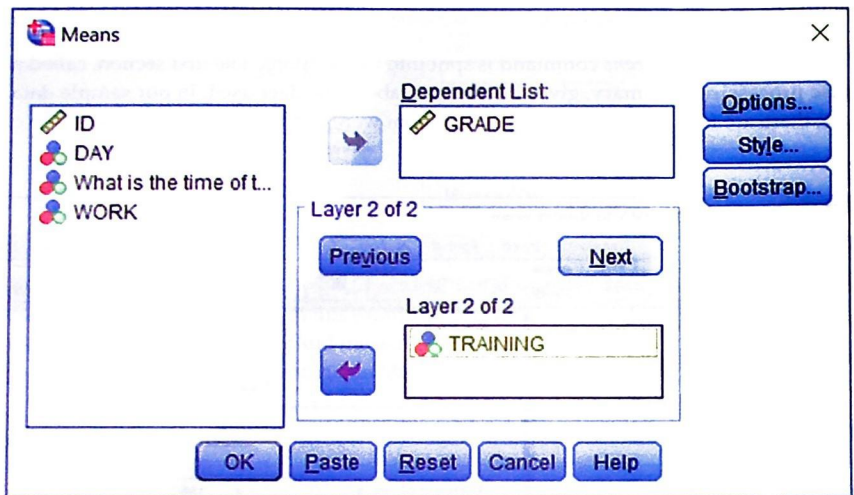
This report lists the name of the **dependent variable** (GRADE) at the top. Every **level** of the **independent variable** (MORNING) is shown in a row in the table. In this example, the **levels** are 0 and 1, labeled No and Yes. Note that if a variable is labeled, the labels will be used instead of the raw values.

The summary statistics given in the report correspond to the data, where the **level** of the **independent variable** is equal to the row heading (e.g., No, Yes). Thus, two participants were included in each row. Morning people had a **mean** GRADE of 78.0 and non-morning people had a **mean** GRADE of 82.5.

An additional row has been added, named **Total**. That row contains the combined data, and the values are the same as they would be if we had run the *Descriptives* command for the variable GRADE.

Extension to More Than One Independent Variable

If you have more than one **independent variable**, SPSS can break down the output even further. Rather than adding more variables to the *Independent List* section of the **dialog box**, you need to add them in a different layer. If you click *Next*, you will be presented with *Layer 2 of 2*, and you can select a second **independent variable** (e.g., TRAINING). Note that SPSS indicates with which layer you are working. Now, when you run the command (by clicking *OK*), you will be given summary statistics for the variable GRADE by each level of MORNING and TRAINING.



Your output will look like the output shown below. You now have two main sections (No and Yes), along with the Total. Now, however, each main section is broken down into subsections (No, Yes, and Total).

Case Processing Summary

	Included		Cases Excluded		Total	
	N	Percent	N	Percent	N	Percent
GRADE * Are you a morning person? *	4	100.0%	0	0.0%	4	100.0%
TRAINING						

Report

GRADE

Are you a morning person?

	TRAINING	Mean	N	Std. Deviation
No	No	80.0000	1	.
	Yes	85.0000	1	.
	Total	82.5000	2	3.53553
Yes	No	73.0000	1	.
	Yes	83.0000	1	.
	Total	78.0000	2	7.07107
Total	No	76.5000	2	4.94975
	Yes	84.0000	2	1.41421
	Total	80.2500	4	5.25198

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 144, W: 664 pt.

The variable you used in Level 1 (MORNING) is the first one listed, and it defines the main sections. The variable you had in Level 2 (TRAINING) is listed second. Thus, the first row represents those participants who were not morning people and who received training. The second row represents participants who were not morning people and did not receive training. The third row represents the total for all participants who were not morning people.

Notice that **standard deviations** are not given for all of the rows. This is because there is only one participant per cell in this example. One problem with using many subsets is that it increases the number of participants that are required to obtain meaningful results. See a research design text or your instructor for more details.

Practice Exercise

Using Practice Dataset 1 in Appendix B, compute the **mean** and **standard deviation** of ages for each value of marital status. What is the average age of the married participants? The single participants? The divorced participants?

Section 3.5 Standard Scores

Description

Standard scores allow the comparison of different scales by transforming the scores into a common scale. The most common standard score is the z-score. A z-score is based on a **standard normal distribution** (i.e., a **mean** of 0 and a **standard deviation** of 1). A z-score, therefore, represents the number of **standard deviations** above or below the **mean** (e.g., a z-score of -1.5 represents a score $1\frac{1}{2}$ **standard deviations** below the **mean** a given score is).

Assumptions

The **standard normal distribution** is the basis for z-scores as normally used. Therefore, the distributions that are converted to z-scores should be normally distributed, and the scales should be either **interval** or **ratio**.

Drawing Conclusions

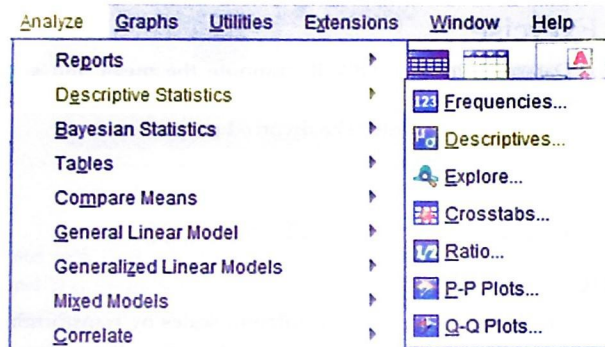
Conclusions based on z-scores consist of the number of **standard deviations** above or below the **mean** a score is. For instance, a student scores 85 on a mathematics exam in a class that has a **mean** of 70 and **standard deviation** of 5. The student's test score is 15 points above the class **mean** ($85 - 70 = 15$). The student's z-score is 3 because she scored three **standard deviations** above the **mean** ($15 \div 5 = 3$). If the same student scores 90 on a reading exam, with a class **mean** of 80 and a **standard deviation** of 10, the z-score will be 1.0 because she is one **standard deviation** above the **mean**. Thus, even though her raw score was higher on the reading test, she actually did better in relation to other students on the mathematics test because her z-score was higher on that test.

SPSS Data Format

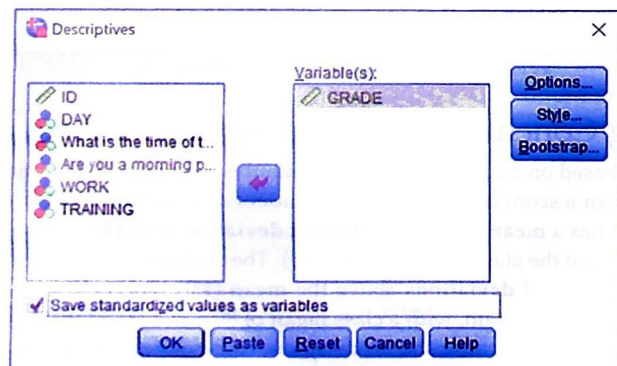
Calculating z-scores requires only a single variable in SPSS. That variable must be numerical.

Running the Command

This example uses the sample data file (SAMPLE.sav) created in Chapters 1 and 2. Computing z-scores is a component of the *Descriptives* command. To access it, click *Analyze*, then *Descriptive Statistics*, then *Descriptives*.



This will bring up the standard dialog box for the *Descriptives* command. Notice the checkbox in the bottom-left corner labeled *Save standardized values as variables*. Check this box and move the variable *GRADE* into the right-hand blank. Then, click *OK* to complete the analysis. You will be presented with the standard output from the *Descriptives* command. Notice that the z-scores are not listed. They were inserted into the *data window* as a new variable.



Switch to the *Data View* window and examine your data file. Notice that a new variable, called *ZGRADE*, has been added. When you asked SPSS to save standardized values, it created a new variable with the same name as your old variable preceded by a *Z*. The z-score is computed for each case and placed in the new variable.

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

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

6 : TRAINING Visible: 8 of 8 Variables

	ID	DAY	TIME	MORNING	GRADE	WORK	TRAINING	ZGRADE	var
1	4593.00	Tues/Thur	Afternoon	No	85.00	No	Yes	90442	
2	1901.00	Mon/Wed/Fri	Morning	Yes	83.00	Part-Time	Yes	52361	
3	8734.00	Tues/Thur	Morning	No	80.00	No	No	-04760	
4	1909.00	Mon/Wed/Fri	Morning	Yes	73.00	Part-Time	No	-1.38043	
5									

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

Reading the Output

After you conducted your analysis, the new variable was created. You can perform any number of subsequent analyses on the new variable.

Practice Exercise

Using Practice Dataset 2 in Appendix B, determine the z-score that corresponds to each employee's salary. Determine the **mean** z-scores for salaries of male employees and female employees. Determine the **mean** z-score for salaries of the total sample.

Chapter 4

Graphing Data

Section 4.1 Graphing Basics

In addition to the frequency distributions, measures of central tendency, and measures of dispersion discussed in Chapter 3, graphing is a useful way to summarize, organize, and reduce your data. It has been said that a picture is worth a thousand words. In the case of complicated datasets, this is certainly true.

With SPSS, it is possible to make publication-quality graphs. One important advantage of using SPSS to create your graphs instead of using other software (e.g., Excel or SigmaPlot) is that the data have already been entered. Thus, duplication is eliminated, and the chance of making a transcription error is reduced.

Section 4.2 Bar Charts, Pie Charts, and Histograms

Description

Bar charts, pie charts, and histograms represent—through the varying heights of bars or sizes of pie pieces—the number of times each score occurs. They are graphical representations of the frequency distributions discussed in Chapter 3.

Drawing Conclusions

The *Frequencies* command produces output that indicates both the number of cases in the sample with a particular value and the percentage of cases with that value. Thus, conclusions drawn should relate only to describing the numbers or percentages for the sample. If the data are at least **ordinal** in nature, conclusions regarding the cumulative percentages and/or percentiles can also be drawn.

SPSS Data Format

You need only one variable to use this command.

Dataset

For the graphing examples, we will use a new set of data. Enter the data that follow by defining the three subject variables in the *Variable View* window: HEIGHT (in inches), WEIGHT (in pounds), and SEX (1 = Male, 2 = Female). When you create the variables, designate HEIGHT and WEIGHT as *Scale* measures and SEX as a *Nominal* measure

(in the far-right column of the *Variable View*). Switch to the *Data View* to enter the data values for the 16 participants. Now use the *Save As* command to save the file, naming it HEIGHT.sav.

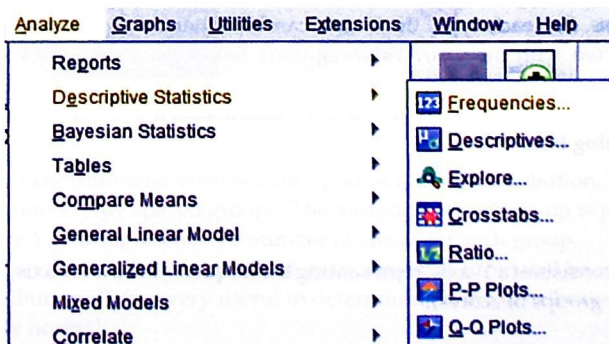
HEIGHT	WEIGHT	SEX
66	150	1
69	155	1
73	160	1
72	160	1
68	150	1
63	140	1
74	165	1
70	150	1
66	110	2
64	100	2
60	95	2
67	110	2
64	105	2
63	100	2
67	110	2
65	105	2

Make sure you have entered the data correctly by calculating a **mean** for each of the three variables (click *Analyze*, then *Descriptive Statistics*, then *Descriptives*). Compare your results with those in the table below.

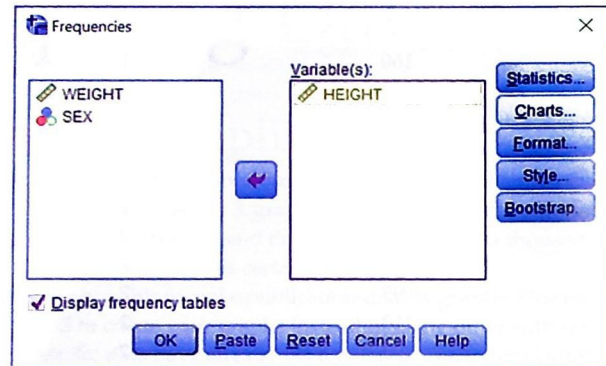
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
HEIGHT	16	60.00	74.00	66.9375	3.90672
WEIGHT	16	95.00	165.00	129.0625	26.34507
SEX	16	1.00	2.00	1.5000	.51640
Valid N (listwise)	16				

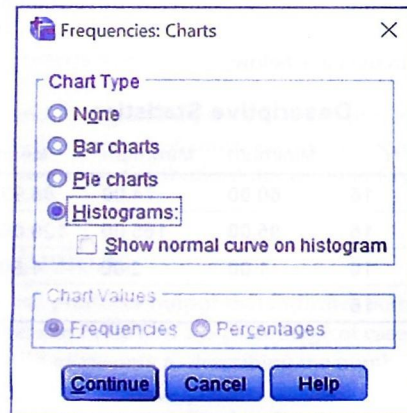
Running the Command



The *Frequencies* command will produce graphical frequency distributions. Click *Analyze*, then *Descriptive Statistics*, then *Frequencies*. You will be presented with the main **dialog box** for the *Frequencies* command, where you can enter the variables for which you would like to create graphs or charts (HEIGHT in this example). See Chapter 3 for other options with this command.



Click the *Charts* button on the right side of the *Frequencies* command to bring up the **Charts dialog box**.

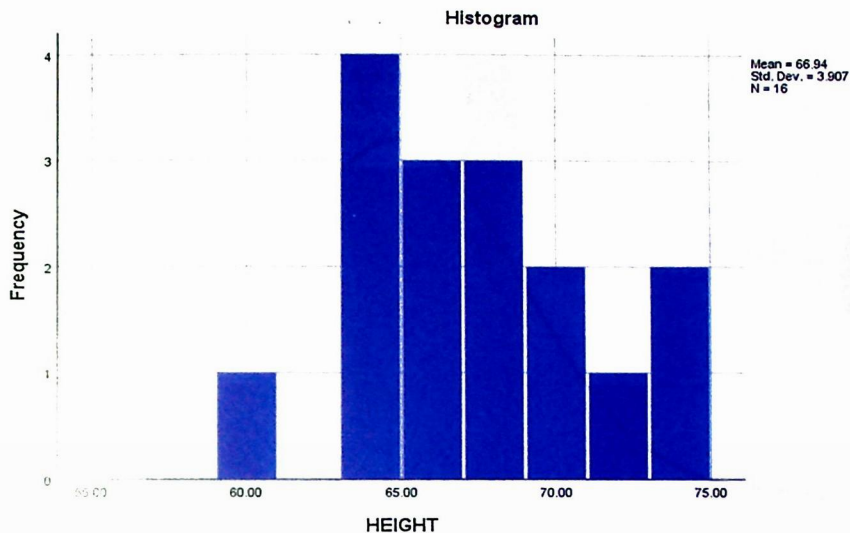


There are three types of charts available with this command: *Bar charts*, *Pie charts*, and *Histograms*. For each type, the Y-axis can be either a frequency count or a percentage (selected with the *Chart Values* option). Select *Bar charts* and click *Continue*. Next, click *OK*.

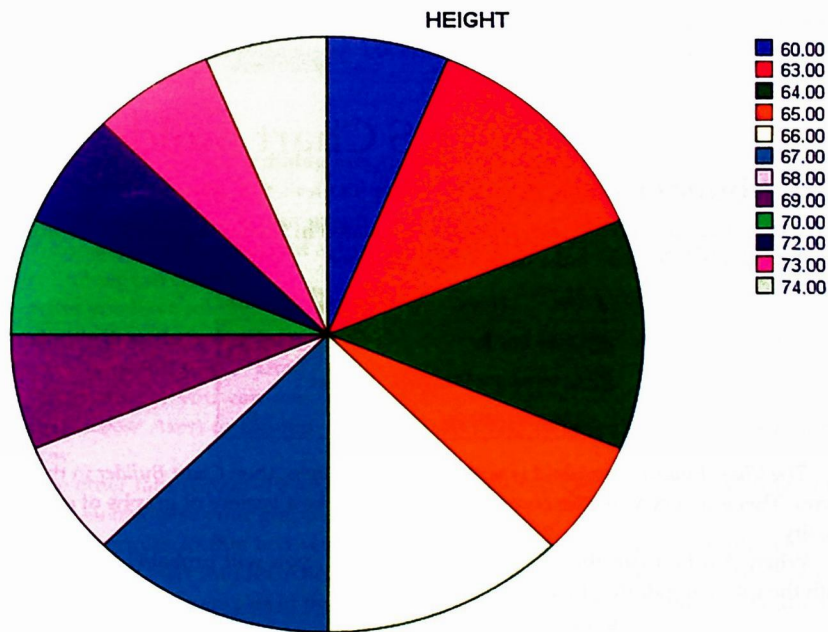
You will receive the charts for any variables selected in the main *Frequencies* command **dialog box**.

Output

The bar chart consists of a Y-axis, representing the frequency, and an X-axis, representing each score (or groups of scores).

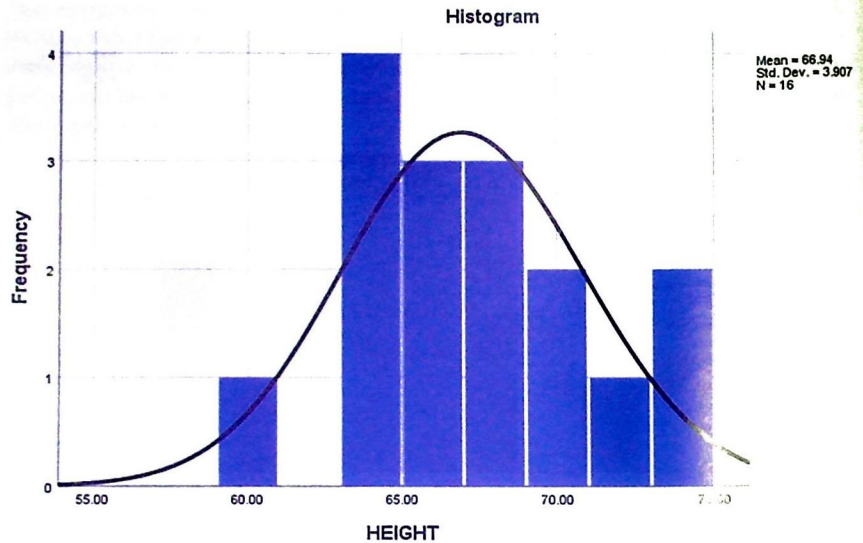


If selected for output, the pie chart shows the percentage of the whole that is represented by each value.



The *Histogram* command creates a grouped frequency distribution. The range of scores is split into evenly spaced groups. The midpoint of each group is plotted on the X-axis, and the Y-axis represents the number of scores for each group.

If you select *Show normal curve on histogram* a normal curve will be superimposed over the distribution. This is very useful in determining if the distribution you have is approximately normal.



Practice Exercise

Use Practice Dataset 1 in Appendix B. After you have entered the data, first construct a histogram that represents the mathematics skills scores and displays a normal curve, and then construct a bar chart that represents the frequencies for the variable AGE.

Section 4.3 The SPSS Chart Builder

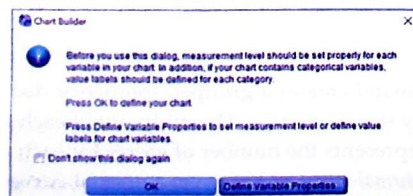
Chart Builder Basics

Make sure that the HEIGHT.sav data file you created in Section 4.2 is open. In order to use the chart builder, you must have a data file open.



The *Chart Builder* command is accessed using *Graphs*, then *Chart Builder* in the submenu. This is a very versatile command that can make a variety of graphs of excellent quality.

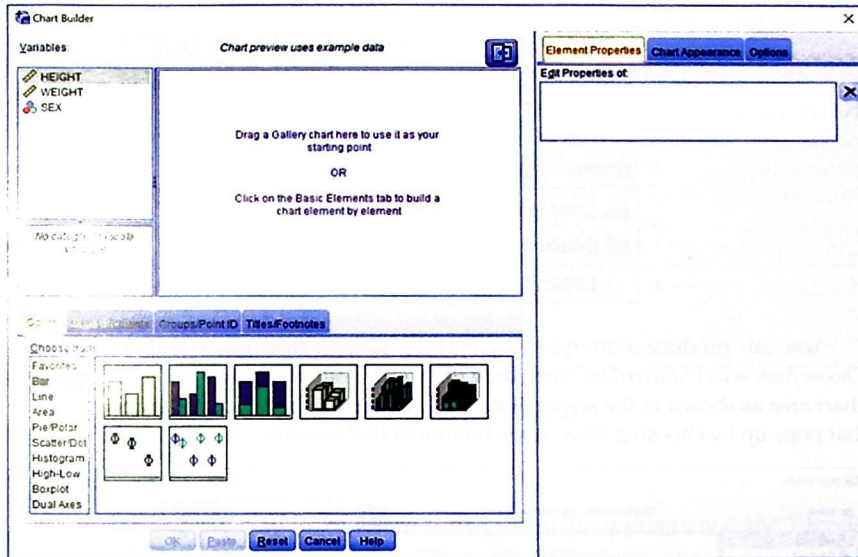
When you first run the *Chart Builder* command, you will probably be presented with the following dialog box:



This dialog box is asking you to ensure that your variables are properly defined. Refer to Sections 1.3 and 2.1 if you had difficulty defining the variables used in

creating the dataset for this example, or to refresh your knowledge of this topic. Click OK.

The Chart Builder allows you to make any kind of graph that is normally used in publication or presentation, and much of it is beyond the scope of this text. However, this text will go over the basics of the Chart Builder so that you can understand its mechanics.



Near the middle of the dialog box, there are four main tabs that let you control the graphs you are making. The first one is the *Gallery* tab. The *Gallery* tab allows you to choose the basic format of your graph.

For instance, the screenshot above shows the different kinds of bar charts that the Chart Builder can create.

After you have selected the basic form of graph that you want using the *Gallery* tab, you simply drag the image from the bottom right of the window up to the main window at the top (where it reads, "Drag a Gallery chart here to use it as your starting point").

Alternatively, you can use the *Basic Elements* tab to drag a coordinate system (labeled *Choose Axes*) to the top window, then drag variables and elements into the window.

The other tabs (*Groups/Point ID* and *Titles/Footnotes*) can be used for adding other standard elements to your graphs.

The examples in this text will cover some of the basic types of graphs you can make with the Chart Builder. After a little experimentation on your own, and once you have mastered the examples in this chapter, you will soon gain a full understanding of the Chart Builder.

Section 4.4 Scatterplots

Description

Scatterplots (also called scattergrams or scatter diagrams) display two values for each case with a mark on the graph. The X-axis represents the value for one variable. The Y-axis represents the value for the second variable.

Assumptions

Both variables should be **interval** or **ratio** scales. If nominal or ordinal data are used, be cautious about your interpretation of the scattergram.

SPSS Data Format

You need two variables to perform this command.

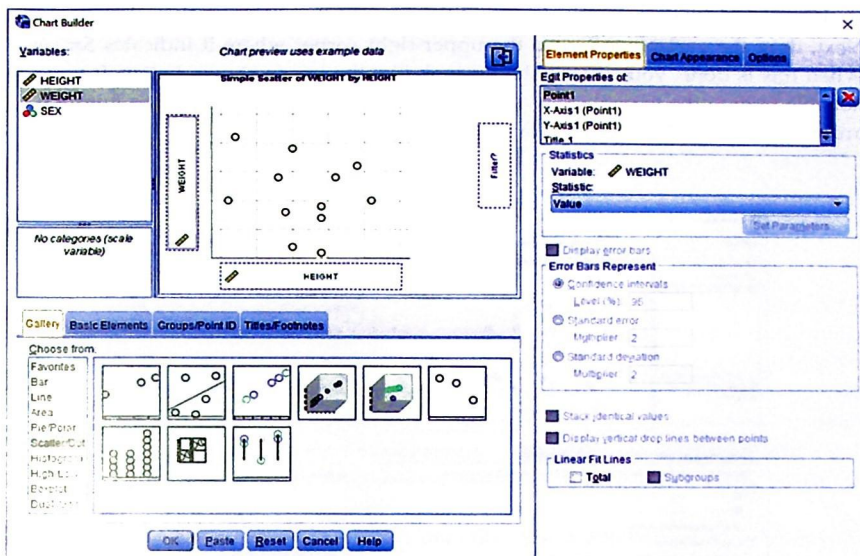
Running the Command



You can produce scatterplots by clicking *Graphs*, then *Chart Builder*. In *Gallery* Choose from select *Scatter/Dot*. Then drag the *Simple Scatter* icon (top-left) up to the main chart area as shown in the screenshot below. Disregard the *Element Properties* window that pops up by choosing *Close* at the bottom of that window.



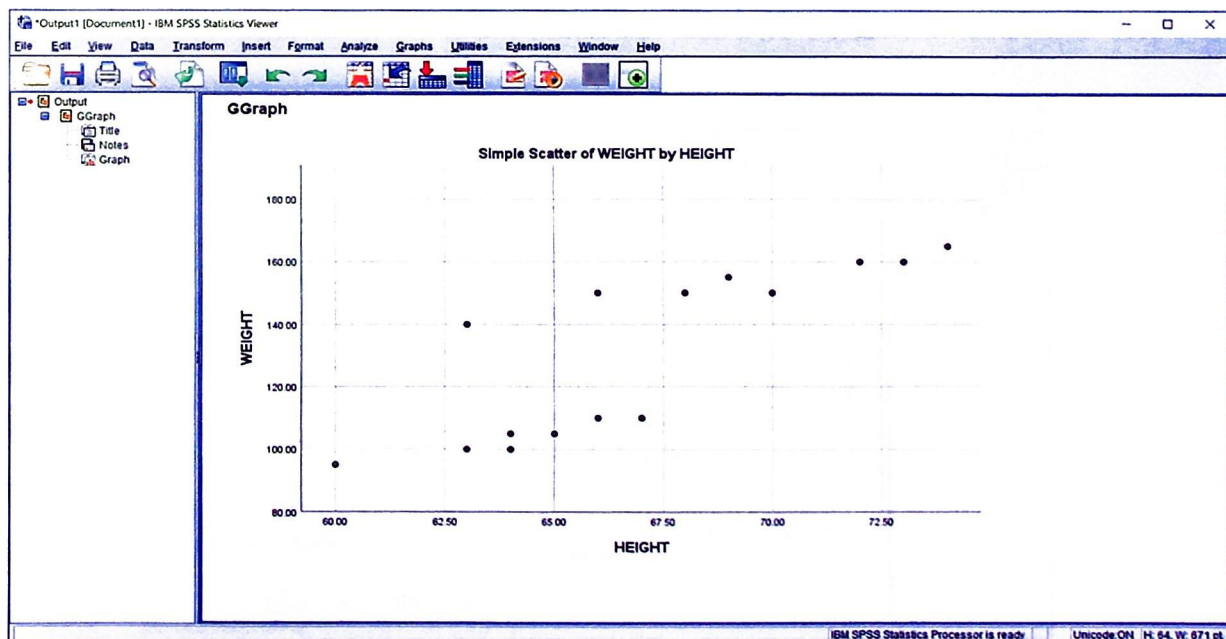
Next, drag the HEIGHT variable to the X-Axis area, and drag the WEIGHT variable to the Y-Axis area. (Remember that standard graphing conventions indicate that **dependent variables** should be Y and **independent variables** should be X. This would mean that we are trying to predict weights from heights.) At this point, your screen should resemble the example shown on the next page. Note that your actual data are *not* shown—just a set of dummy values, which may look different from the pattern shown here.



Click **OK**. You should get your new graph as Output.

Output

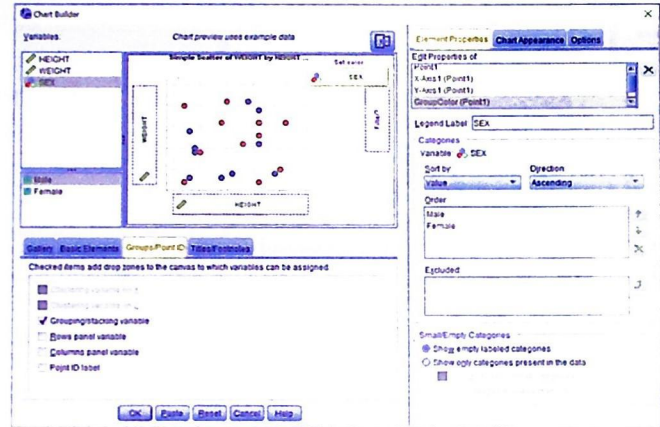
The output will consist of a mark for each participant at the appropriate X and Y levels.



Adding a Third Variable

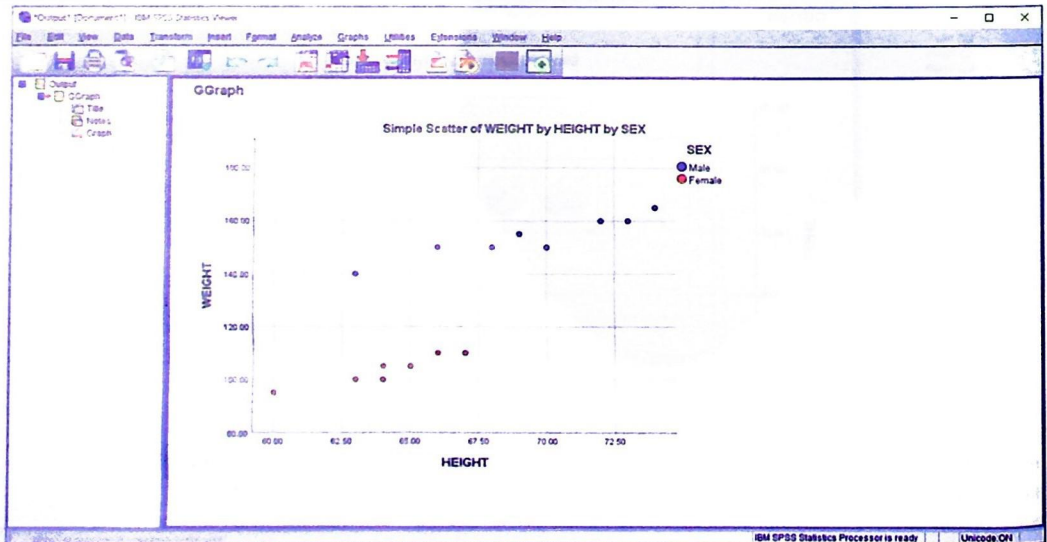
Even though the scatterplot is a two-dimensional graph, it can plot a third variable. To make it do so, select the *Groups/Point ID* tab in the Chart Builder. Click the *Grouping/*

stacking variable option. Again, disregard the *Element Properties* window that pops up. Next, drag the variable *SEX* into the upper-right corner where it indicates *Set color*. When this is done, your screen should look like the image shown below. If you are not able to drag the variable *SEX*, it may be because it is not identified as **nominal** or **ordinal** in the *Variable View* window.



Click *OK* to have SPSS produce the graph.

Now our output will have two different sets of marks. One set represents the male participants, and the second set represents the female participants. These two sets will appear in two different colors on your screen. You can use the *SPSS Chart Editor* (see Section 4.6) to make them different shapes.



Practice Exercise

Use Practice Dataset 2 in Appendix B. Construct a scatterplot to examine the relationship between *SALARY* and *EDUCATION*.

Section 4.5 Advanced Bar Charts

Description

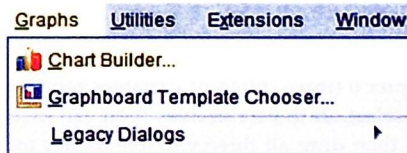
Bar charts can be produced with the *Frequencies* command (see Section 4.2). Sometimes, however, we are interested in a bar chart where the Y-axis is not a frequency. To produce such a chart, we need to use the *Bar charts* command.

SPSS Data Format

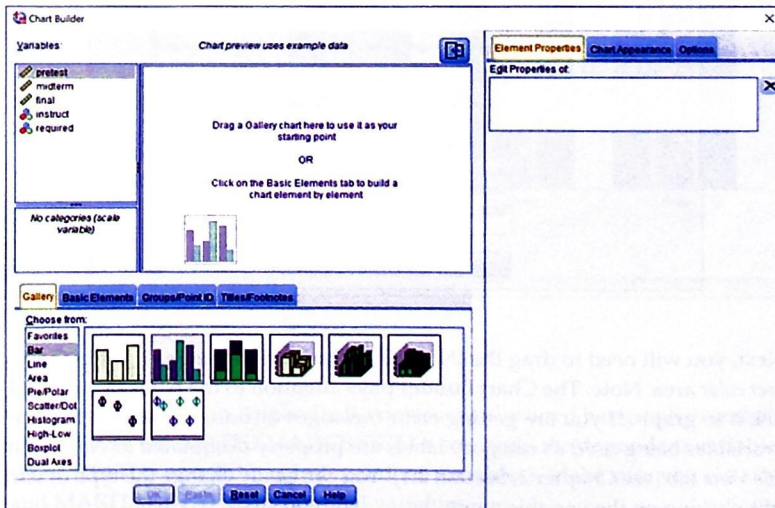
You need at least two variables to perform this command. There are two basic kinds of bar charts—those for between-subjects designs and those for repeated-measures designs. Use the between-subjects method if one variable is the **independent variable** and the other is the **dependent variable** (representing one score for different groups of individuals). Use the repeated-measures method if you have a **dependent variable** for each value of the **independent variable** (e.g., you would have three variables for a design with three values of the **independent variable**). This normally occurs when you make multiple observations over time.

This example uses the GRADES.sav data file, which will be created in Chapter 6. Please see Section 6.4 for the data if you would like to follow along.

Running the Command



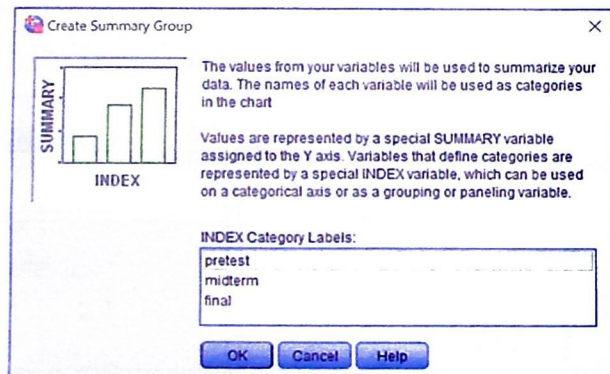
Open the Chart Builder by clicking *Graphs*, then *Chart Builder*. In the *Gallery* tab, select *Bar*. If you had only one **independent variable**, you would select the Simple Bar Chart example (top-left corner). If you have more than one **independent variable** (as in this example), select the Clustered Bar Chart example from the top row.



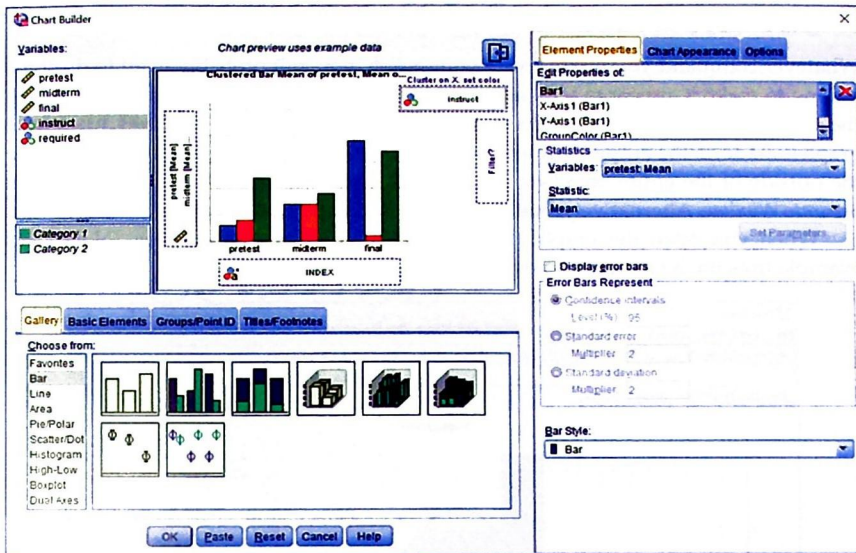
Drag the example to the top working area. Once you do, the working area should look like the screenshot below. (Note that you will need to open the data file you would like to graph in order to run this command.)



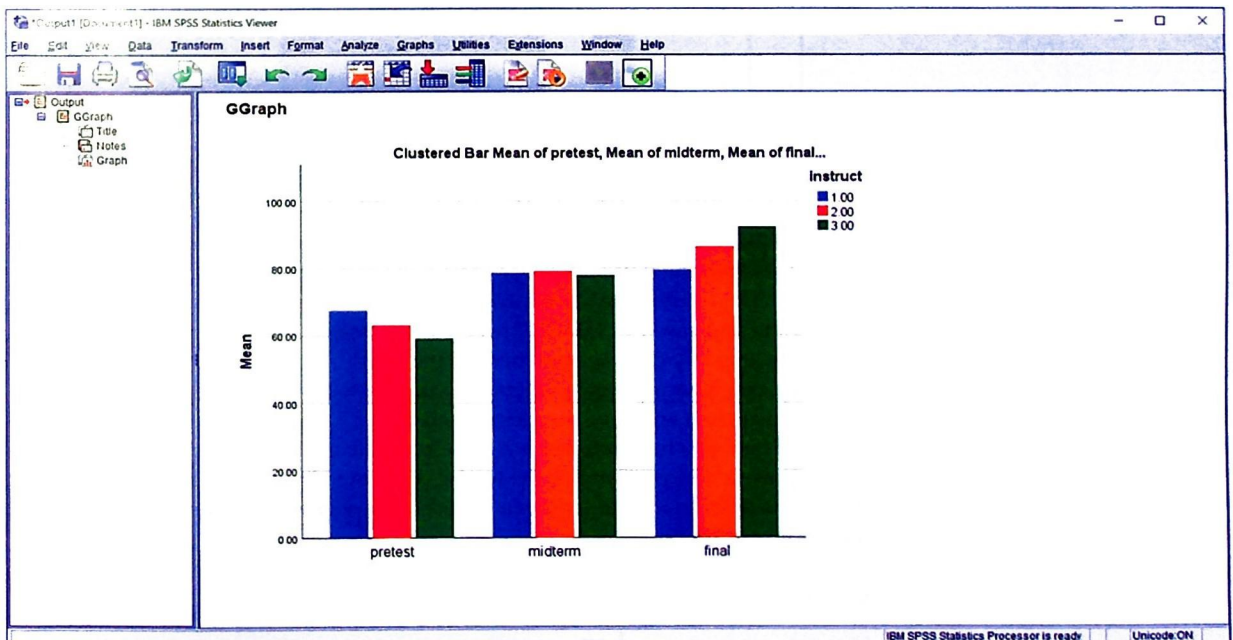
If you are using a repeated-measures design like our example here using GRADES.sav from Chapter 6 (three different variables representing the Y values that we want), you need to select all three variables (you can <Ctrl>-click them to select multiple variables) and then drag all three variable names to the Y-Axis area. When you do, you will be given the confirmation message shown. Click OK.



Next, you will need to drag the INSTRUCT variable to the top-right in the *Cluster on X: set color* area. Note: The Chart Builder pays attention to the types of variables that you ask it to graph. If you are getting error messages or unusual results, be sure that your variables being used as category labels are properly designated as *Nominal* in the *Variable View* tab (see Chapter 2, Section 2.1). You can easily change the type of variable by right-clicking on the variable name.



Output



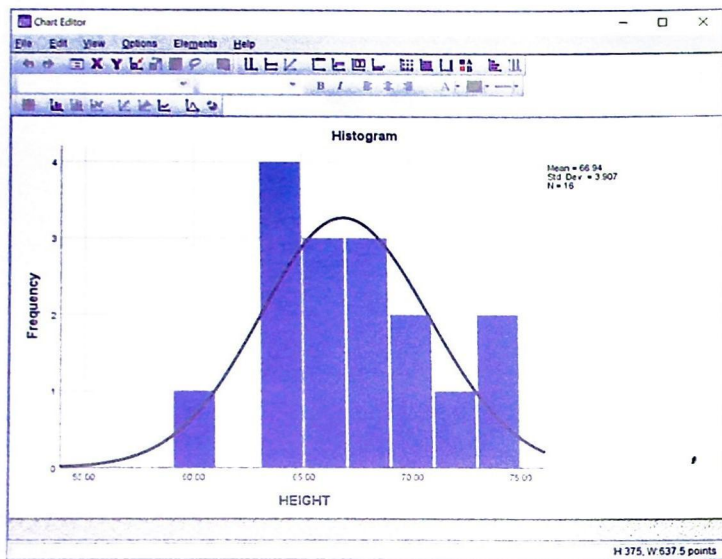
Practice Exercise

Using Practice Dataset 1 in Appendix B, construct a clustered bar graph examining the relationship between MATHEMATICS SKILLS scores (as the **dependent variable**) and MARITAL STATUS and SEX (as **independent variables**). Make sure you classify both SEX and MARITAL STATUS as nominal variables.

Section 4.6 Editing SPSS Graphs

Whatever command you use to create your graph, you will probably want to do some editing to make it appear exactly as you want it to look. In SPSS, you do this in much the same way that you edit graphs in other software programs (e.g., Excel). After your graph is made, in the **output window**, select your graph (this will create handles around the outside of the entire object) and right-click. Then, click *Edit Content*, and click *In Separate Window*. Alternatively, you can double-click on the graph to open it for editing.

When you open the graph, the *Chart Editor* window will appear. (Note: This example uses the histogram created in Section 4.2.)



Once *Chart Editor* is open, you can easily edit each element of the graph. To select an element, click on the relevant spot on the graph. For instance, if you have added a title to your graph ("Histogram" in the example shown above, which was created earlier in this chapter and saved as HEIGHT.sav), you may select the element representing the title of the graph by clicking anywhere on the title.

Once you have selected an element, you can tell whether the correct element is selected because it will have handles around it.

If the item you have selected is a text element (e.g., the title of the graph), a cursor will be present and you can edit the text as you would in a word processing program. If you would like to change another attribute of the element (e.g., the color or font size), use the Properties box.

With a little practice, you can make excellent graphs using SPSS. Once your graph is formatted the way you want it, simply select *File*, then *Close*.



Chapter 5

Prediction and Association

Section 5.1 Pearson Correlation Coefficient

Description

The Pearson correlation coefficient (sometimes called the *Pearson product-moment correlation coefficient* or simply the *Pearson r*) determines the strength of the linear relationship between two variables.

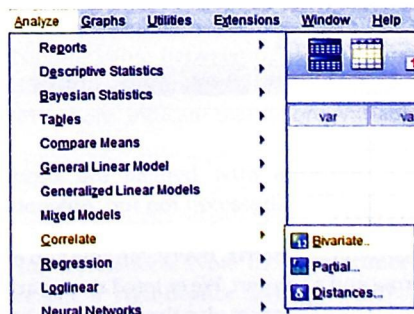
Assumptions

Both variables should be measured on **interval** or **ratio scales** (or as a **dichotomous** nominal variable). If a relationship exists between them, that relationship should be linear. Because the Pearson correlation coefficient is computed with z-scores, both variables should also be normally distributed. If your data do not meet these assumptions, consider using the Spearman *rho* correlation coefficient instead.

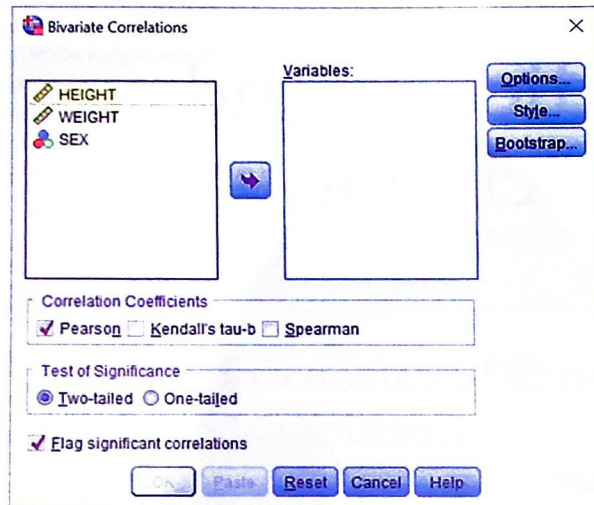
SPSS Data Format

Two variables are required in your SPSS data file. Each subject must have data for both variables.

Running the Command

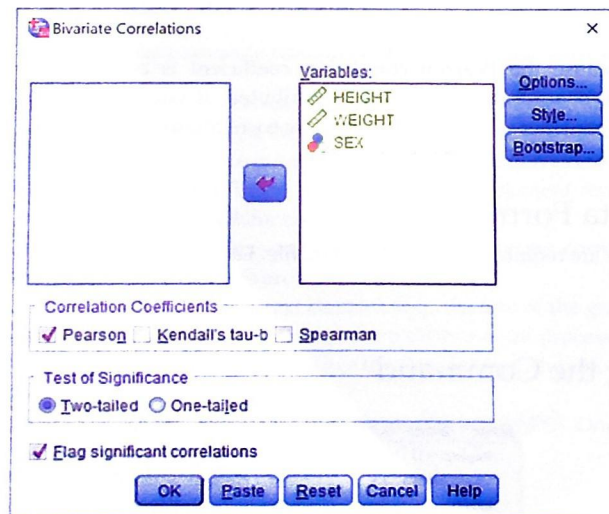


To select the Pearson correlation coefficient, click *Analyze*, then *Correlate*, then *Bivariate* (bivariate refers to two variables). This will bring up the Bivariate Correlations dialog box. This example uses the HEIGHT.sav data file entered at the start of Chapter 4.



Move at least two variables from the box at the left into the box at the right by using the transfer arrow (or by double-clicking each variable). Make sure that a check is in the *Pearson* box under *Correlation Coefficients*. It is acceptable to move more than two variables.

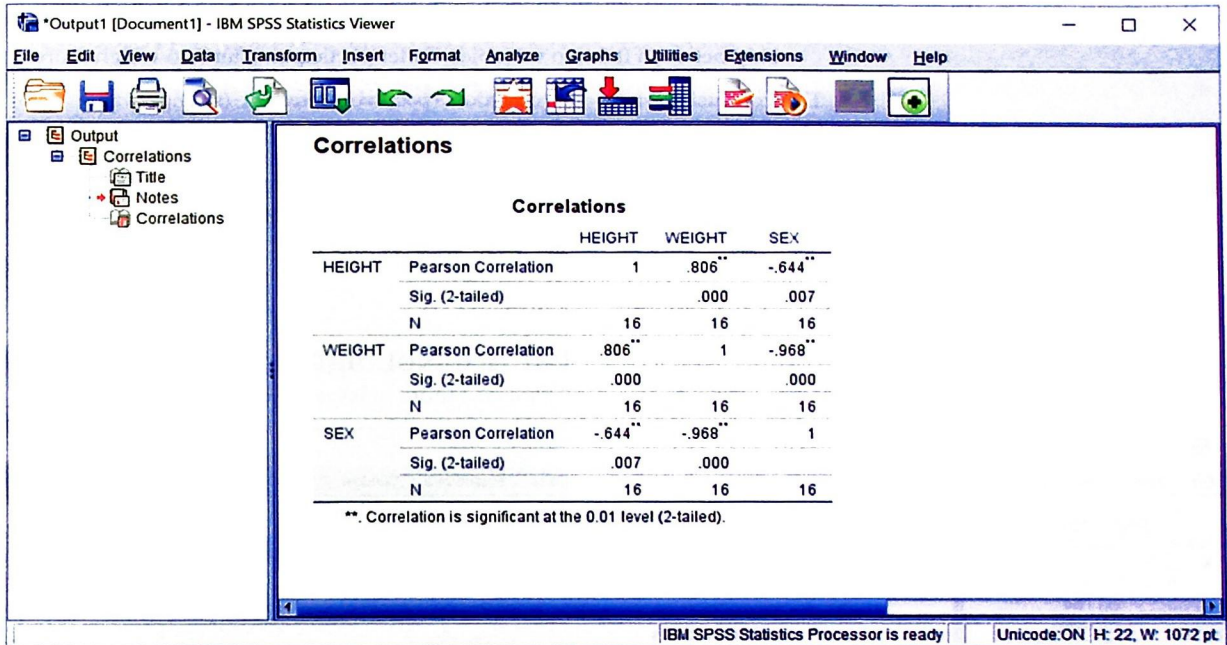
For our example, we will move all three variables over and click *OK*.



Reading the Output

The output consists of a **correlation matrix**. Every variable you entered in the command is represented as both a row and a column. We entered three variables in our command. Therefore, we have a 3×3 table. There are also three rows in each cell—the correlation,

the **significance** level, and the N . If a correlation is significant at less than the .05 level, a single * will appear next to the correlation. If it is significant at the .01 level or lower, ** will appear next to the correlation. For instance, all of the correlations in the output above have a **significance** level of $< .01$, so they are flagged with ** to indicate that they are less than .01.



Correlations

		HEIGHT	WEIGHT	SEX
HEIGHT	Pearson Correlation	1	.806**	-.644**
	Sig. (2-tailed)		.000	.007
	N	16	16	16
WEIGHT	Pearson Correlation	.806**	1	-.968**
	Sig. (2-tailed)	.000		.000
	N	16	16	16
SEX	Pearson Correlation	-.644**	-.968**	1
	Sig. (2-tailed)	.007	.000	
	N	16	16	16

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

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 22, W: 1072 pt

To read the correlations, select a row and a column. For instance, the correlation between height and weight is determined through selection of the WEIGHT row and the HEIGHT column (.806). We get the same answer by selecting the HEIGHT row and the WEIGHT column. The correlation between a variable and itself is always 1, so there is a diagonal set of 1s.

Drawing Conclusions

The correlation coefficient will be between -1.0 and $+1.0$. Coefficients close to 0.0 represent a weak relationship. Coefficients close to 1.0 or -1.0 represent a strong relationship. Generally, correlations with an absolute value greater than 0.7 are considered strong. Correlations with an absolute value less than 0.3 are considered weak. Correlations with an absolute value between 0.3 and 0.7 are considered moderate. Positive correlations indicate that as one variable gets larger, the other variable also gets larger. Negative correlations indicate that as one variable gets larger, the other variable gets smaller.

Significant correlations are flagged with asterisks. A significant correlation indicates a reliable relationship, but not necessarily a strong correlation. With enough participants, a very small correlation can be significant. See Appendix A for a discussion of **effect sizes** for correlations. Note the **significance** level of .000 for some relationships. This is, in fact, a **significance** level of $< .001$. The actual alpha level rounds down to .000, but it is not zero.

Phrasing Results That Are Significant

In the preceding example, we obtained a correlation of .806 between HEIGHT and WEIGHT. A correlation of .806 is a strong positive correlation, and it is significant at the .001 level. Thus, we could state the following in a results section:

A Pearson correlation coefficient was calculated for the relationship between participants' height and weight. A strong positive correlation was found ($r(14) = .806, p < .001$), indicating a significant linear relationship between the two variables. Taller participants tend to weigh more.

The conclusion states the direction (positive), strength (strong), value (.806), degrees of freedom (14), and **significance level** ($< .001$) of the correlation. In addition, a statement of direction is included (taller is heavier).

Note that the degrees of freedom given in parentheses is 14. The output indicates an N of 16. While most SPSS procedures give degrees of freedom, the *Correlation* command gives only the N (the number of pairs). For a correlation, the degrees of freedom is $N - 2$.

Phrasing Results That Are Not Significant

The screenshot shows the IBM SPSS Statistics Viewer interface. The main window displays the results of a 'Correlations' command. The output is presented in a table format with the following data:

		ID	GRADE
ID	Pearson Correlation	1	.217
	Sig. (2-tailed)		.783
	N	4	4
GRADE	Pearson Correlation	.217	1
	Sig. (2-tailed)	.783	
	N	4	4

The status bar at the bottom of the window indicates 'IBM SPSS Statistics Processor is ready' and 'Unicode:ON | H: 22, W: 665 pt'.

Using our SAMPLE.sav dataset from the previous chapters, we can calculate a correlation between ID and GRADE. If we do so, we get the output shown here. The correlation has a **significance level** of .783. Thus, we could write the following in a results section (note that the degrees of freedom is $N - 2$):

A Pearson correlation was calculated examining the relationship between participants' ID numbers and grades. A weak correlation that was not significant was found ($r(2) = .217, p > .05$). ID number is not related to grade in the course.

Practice Exercise

Use Practice Dataset 2 in Appendix B. Determine the value of the Pearson correlation coefficient for the relationship between SALARY and YEARS OF EDUCATION, and phrase your results.

Section 5.2 Spearman Correlation Coefficient

Description

The Spearman correlation coefficient determines the strength of the relationship between two variables. It is a nonparametric procedure. Therefore, it is weaker than the Pearson correlation coefficient, but it can be used in more situations.

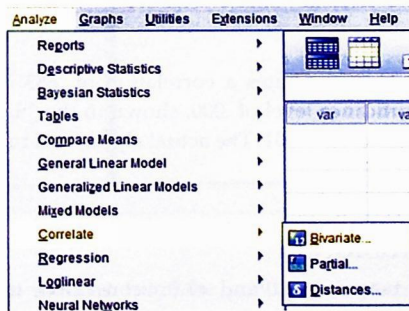
Assumptions

Because the Spearman correlation coefficient functions on the basis of the ranks of data, it requires **ordinal** (or **interval** or **ratio**) data for both variables. They do not need to be normally distributed.

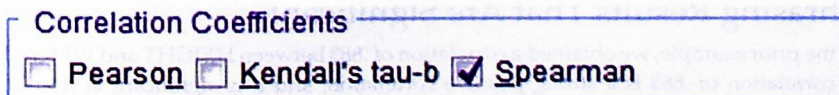
SPSS Data Format

Two variables are required in your SPSS data file. Each subject must provide data for both variables.

Running the Command



Using the HEIGHT.sav file created in Chapter 4, click *Analyze*, then *Correlate*, then *Bivariate*. This will bring up the main dialog box for Bivariate Correlations (just like the Pearson correlation). About halfway down the dialog box, there is a section for indicating the type of correlation you will compute. You can select as many correlations as you want. For our example, remove the check in the *Pearson* box (by clicking on it) and click on the *Spearman* box.



Use the variables HEIGHT and WEIGHT. This is also one of the few commands that allows you to choose a one-tailed test, if desired.

Reading the Output

The output is essentially the same as for the Pearson correlation. Each pair of variables has its correlation coefficient indicated twice. The Spearman ρ can range from -1.0 to $+1.0$, just like the Pearson r .

The screenshot shows the IBM SPSS Statistics Viewer window. The main pane displays the 'Nonparametric Correlations' output. The output is structured as follows:

Correlations				
			HEIGHT	WEIGHT
Spearman's rho	HEIGHT	Correlation Coefficient	1.000	.883**
		Sig. (2-tailed)	.	.000
		N	16	16
	WEIGHT	Correlation Coefficient	.883**	1.000
		Sig. (2-tailed)	.000	.
		N	16	16

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

The output listed above indicates a correlation of .883 between HEIGHT and WEIGHT. Note the significance level of .000, shown in the "Sig. (2-tailed)" row. This is, in fact, a significance level of $< .001$. The actual alpha level rounds down to .000, but it is not zero.

Drawing Conclusions

The correlation will be between -1.0 and $+1.0$. Scores close to 0.0 represent a weak relationship. Scores close to 1.0 or -1.0 represent a strong relationship. Significant correlations are flagged with asterisks. A significant correlation indicates a reliable relationship, but not necessarily a strong correlation. With enough participants, a very small correlation can be significant. Generally, correlations greater than 0.7 are considered strong. Correlations less than 0.3 are considered weak. Correlations between 0.3 and 0.7 are considered moderate.

Phrasing Results That Are Significant

In the prior example, we obtained a correlation of .883 between HEIGHT and WEIGHT. A correlation of .883 is a strong positive correlation, and it is significant at the .001 level. Thus, we could state the following in a results section:

A Spearman ρ correlation coefficient was calculated for the relationship between participants' height and weight. A strong positive correlation was found ($\rho(14) = .883, p < .001$), indicating a significant relationship between the two variables. Taller participants tend to weigh more.

The conclusion states the direction (positive), strength (strong), value (.883), degrees of freedom (14), and significance level ($< .001$) of the correlation. In addition, a statement of direction is included (taller is heavier). Note that the degrees of freedom given in parentheses is 14. The output indicates an N of 16. For a correlation, the degrees of freedom is $N - 2$.

Phrasing Results That Are Not Significant

The screenshot shows the IBM SPSS Statistics Viewer interface. The main window displays the 'Nonparametric Correlations' output. The output is a table showing the correlation between 'ID' and 'GRADE'. The correlation coefficient is .000, and the significance level (Sig. (2-tailed)) is 1.000. The sample size (N) for both variables is 4.

		ID	GRADE
Spearman's rho	ID	Correlation Coefficient	1.000 .000
		Sig. (2-tailed)	. 1.000
		N	4 4
GRADE	GRADE	Correlation Coefficient	.000 1.000
		Sig. (2-tailed)	1.000 .
		N	4 4

Using our SAMPLE.sav dataset from the previous chapters, we could calculate a Spearman ρ correlation between ID and GRADE. If we did so, we would get the output shown here. The correlation coefficient equals .000 and has a significance level of 1.000. Note that though this value is rounded up and is not, in fact, exactly 1.000, we could state the following in a results section:

A Spearman ρ correlation coefficient was calculated for the relationship between a subject's ID number and grade. An extremely weak correlation that was not significant was found ($r(2) = .000, p > .05$). ID number is not related to grade in the course.

Practice Exercise

Use Practice Dataset 2 in Appendix B. Determine the strength of the relationship between salary and job classification by calculating the Spearman r_{ho} correlation.

Section 5.3 Simple Linear Regression

Description

Simple linear regression allows for the prediction of one variable from another.

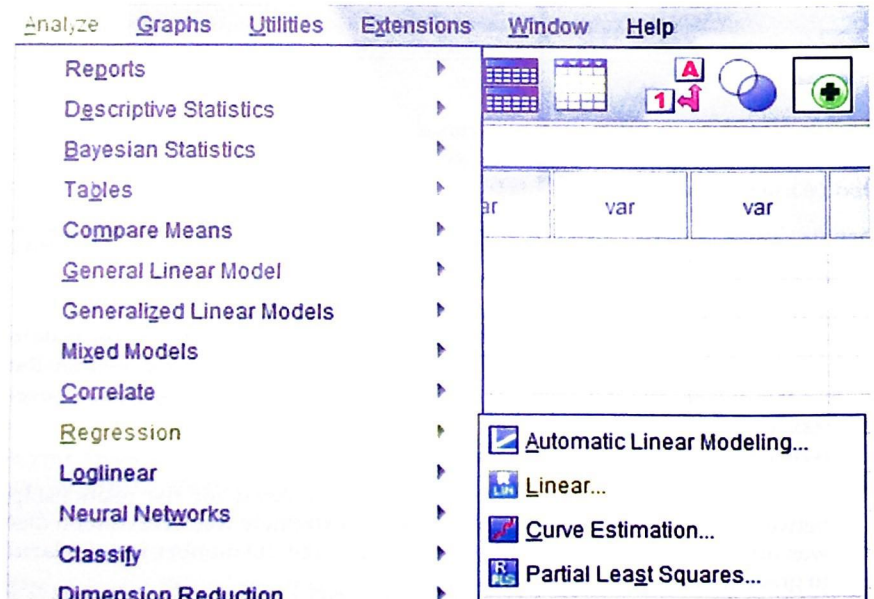
Assumptions

Simple linear regression assumes that both variables are **interval-** or **ratio-scaled**. In addition, the **dependent variable** should be normally distributed around the prediction line. This, of course, assumes that the variables are related to each other linearly. Typically, both variables should be normally distributed. **Dichotomous variables** (variables with only two levels) are also acceptable as **independent variables**.

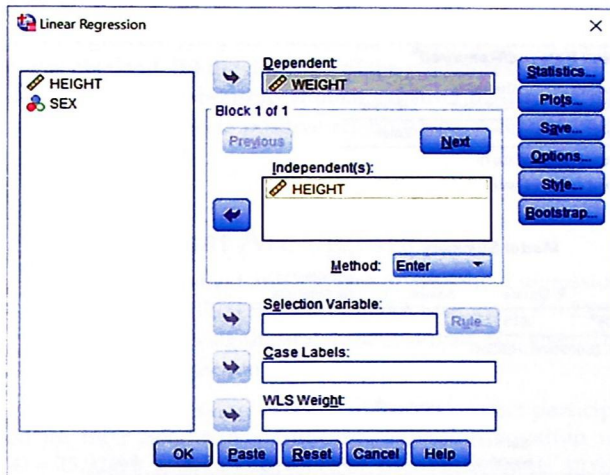
SPSS Data Format

Two variables are required in the SPSS data file. Each subject must contribute to both values.

Running the Command



Returning to the HEIGHT.sav data file, click *Analyze*, then *Regression*, then *Linear*. This will bring up the main dialog box for Linear Regression, shown below. On the left side of the dialog box is a list of the variables in your data file. On the right are blocks for the **dependent variable** (the variable we are trying to predict) and the **independent variable** (the variable from which we are predicting).



We are interested in predicting someone's weight on the basis of his or her height. Thus, we should place the variable **WEIGHT** in the **dependent variable** block and the variable **HEIGHT** in the **independent variable** block. Then, we can click **OK** to run the analysis.

Reading the Output

For simple linear regressions, we are interested in three components of the output. The first is called the Model Summary, and it occurs after the Variables Entered/Removed section. For our example, you should see this output. *R* Square (called the **coefficient of determination**) gives you the proportion of the **variance** of your **dependent variable** (**WEIGHT**) that can be explained by variation in your **independent variable** (**HEIGHT**). Thus, 64.9 percent of the variation in weight can be explained by differences in height (taller individuals weigh more).

The **standard error of estimate** gives you a measure of dispersion for your prediction equation. When the prediction equation is used, 68 percent of the data will fall within one **standard error of estimate** (predicted) value. Just over 95 percent will fall within two standard errors. Thus, in the previous example, 95 percent of the time, our estimated weight will be within 32.296 pounds of being correct (i.e., $2 \times 16.148 = 32.296$).

The second part of the output that we are interested in is the ANOVA summary table. The important number here is the **significance** level in the rightmost column. If that value is less than .05, then we have a significant linear regression. If it is larger than .05, we do not. For more information on reading ANOVA tables, refer to the sections on ANOVA in Chapter 7.

The final section of the output is the table of coefficients. This is where the actual prediction equation can be found.

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 22, W: 664 pt.

*Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

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

Regression

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	HEIGHT ^b		Enter

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

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.806 ^a	.649	.624	16.14801

a. Predictors: (Constant), HEIGHT

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6760.323	1	6760.323	25.926	.000 ^b
	Residual	3650.614	14	260.758		
	Total	10410.938	15			

a. Dependent Variable: WEIGHT
b. Predictors: (Constant), HEIGHT

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-234.681	71.552		-3.280	.005
	HEIGHT	5.434	1.067	.806	5.092	.000

a. Dependent Variable: WEIGHT

In most texts, you learn that $Y' = a + bX$ is the regression equation. Y' (pronounced "Y prime") is your **dependent variable** (primes are normally predicted values or dependent variables), and X is your **independent variable**. In SPSS output, the values of both a and b are found in the B column. The first value, -234.681 , is the value of a (labeled Constant). The second value, 5.434 , is the value of b (labeled with the name of the **independent variable**). Thus, our prediction equation for the example above is $WEIGHT' = -234.681 + 5.434(HEIGHT)$. In other words, the average subject who is an inch taller than another subject weighs 5.434 pounds more. A person who is 60 inches tall should weigh $-234.681 + 5.434(60) = 91.359$ pounds. Given our earlier discussion

of **standard error of estimate**, 95 percent of individuals who are 60 inches tall will weigh between 59.063 ($91.359 - 32.296 = 59.063$) and 123.655 ($91.359 + 32.296 = 123.655$) pounds.

Drawing Conclusions

Conclusions from regression analyses indicate (a) whether or not a significant prediction equation was obtained, (b) the direction of the relationship, and (c) the equation itself. The direction of the relationship is obtained from the sign of the Beta coefficient. Positive coefficients indicate positive relationships. Negative coefficients indicate negative relationships.

Phrasing Results That Are Significant

In the earlier example, we obtained an *R* Square of .649 and a regression equation of $WEIGHT' = -234.681 + 5.434(HEIGHT)$. The ANOVA resulted in $F = 25.926$ with 1 and 14 degrees of freedom. The *F* is significant at the less than .001 level. Thus, we could state the following in a results section:

A simple linear regression was calculated to predict participants' weight based on their height. A significant regression equation was found ($F(1,14) = 25.926, p < .001$), with an R^2 of .649. Participants' predicted weight is equal to $-234.68 + 5.43(HEIGHT)$ pounds when height is measured in inches. Participants' average weight increased 5.43 pounds for each inch of height.

The conclusion states the direction (increase), strength (.649), value (25.926), degrees of freedom (1,14), and **significance** level ($< .001$) of the regression. In addition, a statement of the equation itself is included.

Phrasing Results That Are Not Significant

If the ANOVA is not significant (this example attempts to predict GRADE from TRAINING using the SAMPLE.sav dataset), the section of the output labeled *Sig.* for the ANOVA will be greater than .05, and the regression equation will not be significant. A results section might include the following statement:

A simple linear regression was calculated to predict participants' grades from whether or not they received training. The regression equation was not significant ($F(1,2) = 4.245, p > .05$) with an R^2 of .68. Training is not a significant predictor of grades.

Note that for results that are not significant, the ANOVA results and R^2 results are given, but the regression equation is not.

*Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

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

Regression

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	TRAINING ^b		Enter

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

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.824 ^a	.680	.520	3.64005

a. Predictors: (Constant), TRAINING

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56.250	1	56.250	4.245	.176 ^b
	Residual	26.500	2	13.250		
	Total	82.750	3			

a. Dependent Variable: GRADE
b. Predictors: (Constant), TRAINING

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	76.500	2.574		29.721	.001
	TRAINING	7.500	3.640	.824	2.060	.176

a. Dependent Variable: GRADE

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 22, W: 664 pt

Practice Exercise

Use Practice Dataset 2 in Appendix B. If we want to predict salary from years of education, what salary would you predict for someone with 12 years of education? What salary would you predict for someone with a college education (16 years)?

Section 5.4 Multiple Linear Regression

Description

The multiple linear regression analysis allows the prediction of one variable from several other variables.

Assumptions

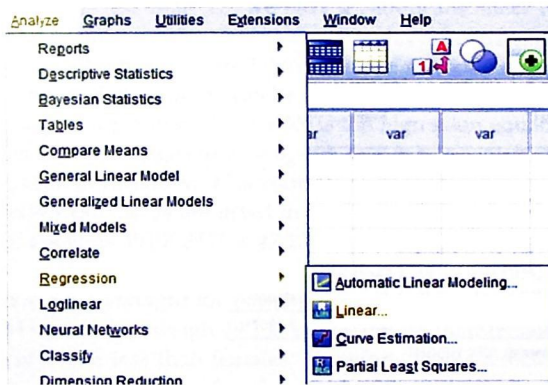
Multiple linear regression assumes that all variables are **interval-** or **ratio-scaled**. In addition, the **dependent variable** should be normally distributed around the prediction line. This, of course, assumes that the variables are related to each other linearly. All variables should be normally distributed. **Dichotomous variables** (e.g., SEX in the example below) are also acceptable as **independent variables**.

SPSS Data Format

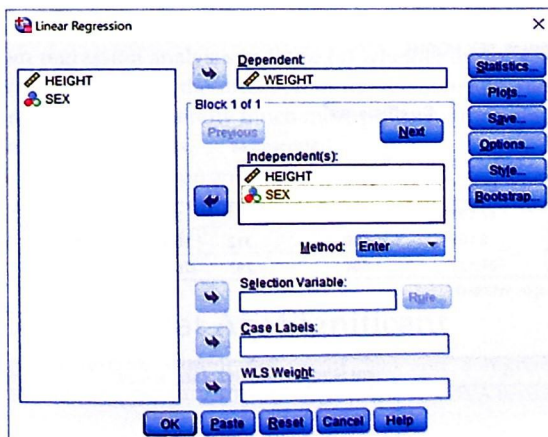
At least three variables are required in the SPSS data file. Each subject must provide data for all variables.

Running the Command

Click *Analyze*, then *Regression*, then *Linear*. This will bring up the main **dialog box** for Linear Regression. On the left side of the **dialog box** is a list of the variables in your data file. (We are using the HEIGHT.sav data file from the start of this chapter.) On the right side of the dialog box are blanks for the **dependent variable** (the variable you are trying to predict) and the **independent variables** (the variables from which you are predicting).



We are interested in predicting someone's weight based on his or her height and sex. We believe that both sex and height are related to weight. Thus, we should place the **dependent variable** WEIGHT in the *Dependent* block and the **independent variables** HEIGHT and SEX in the *Independent(s)* block.



This will perform an analysis to determine if WEIGHT can be predicted from SEX and/or HEIGHT. There are several methods SPSS can use to conduct this analysis. These can be selected with the *Method* box. The most widely used is *Enter* (the default), which puts all the variables in the equation, whether or not they are significant. Other methods can be selected by clicking on the down arrow next to the word *Enter*. The other methods use various means to enter only those variables that are significant predictors. In this case, we will use the default. Click OK to run the analysis.

Method: **Enter** ▼

Reading the Output

The screenshot shows the IBM SPSS Statistics Viewer window with the following output:

Regression

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	SEX, HEIGHT ^b		Enter

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

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.997 ^a	.993	.992	2.29571

a. Predictors: (Constant), SEX, HEIGHT

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10342.424	2	5171.212	981.202	.000 ^b
	Residual	68.514	13	5.270		
	Total	10410.938	15			

a. Dependent Variable: WEIGHT
b. Predictors: (Constant), SEX, HEIGHT

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	47.138	14.843		3.176	.007
	HEIGHT	2.101	.198	.312	10.588	.000
	SEX	-.39.133	1.501	-.767	-26.071	.000

a. Dependent Variable: WEIGHT

Double click to edit Text | IBM SPSS Statistics Processor is ready | Unicode.ON | H: 22, W: 664 pt.

For multiple linear regression, there are three components of the output in which we are interested. The first is called the Model Summary, which is found after the Variables Entered/Removed section. For our example, you should get the output above.

R Square (called the **coefficient of determination**) tells you the proportion of the variance in the dependent variable (WEIGHT) that can be explained by variation in the independent variables (HEIGHT and SEX, in this case). Thus, 99.3 percent of the variation in weight can be explained by differences in height and sex (taller individuals weigh more, and men weigh more). Note that when a second variable is added, our *R* Square goes up from .649 to .993. The .649 was obtained using the Simple Linear Regression example in Section 5.3.

The **standard error of the estimate** gives you a margin of error for the prediction equation. Using the prediction equation, 68 percent of the data will fall within one **standard error of estimate** (predicted) value. Just over 95 percent will fall within two **standard errors of estimate**. Thus, in the example above, 95 percent of the time our estimated weight will be within 4.591 (2.29571×2) pounds of being correct. In our Simple Linear Regression example in Section 5.3, this number was 32.296. Note the higher degree of accuracy.

The second part of the output that we are interested in is the ANOVA summary table. For more information on reading ANOVA tables, refer to the sections on ANOVA in Chapter 7. For now, the important number is the **significance** in the rightmost column. If that value is less than .05, we have a significant linear regression. If it is larger than .05, we do not.

The final section of output we are interested in is the table of coefficients. This is where the actual prediction equation can be found.

In most texts, you learn that $Y' = a + bX$ is the regression equation. For multiple regression, our equation changes to $Y' = B_0 + B_1X_1 + B_2X_2 + \dots + B_z X_z$ (where z is the number of independent variables). Y' is your **dependent variable**, and the X s are your **independent variables**. The B s are listed in a column. Thus, our prediction equation for the example above is $\text{WEIGHT}' = 47.138 - 39.133(\text{SEX}) + 2.101(\text{HEIGHT})$ (where SEX is coded as 1 = Male, 2 = Female, and HEIGHT is in inches). In other words, the average difference in weight for participants who differ by one inch in height is 2.101 pounds. Males tend to weigh 39.133 pounds more than females. (Males have a value of SEX that is one less than females. Therefore, their predicted weight will be $(-1)(-39.133) = 39.133$ different.) A female who is 60 inches tall should weigh $47.138 - 39.133(2) + 2.101(60) = 94.932$ pounds. Given our earlier discussion of the **standard error of estimate**, 95 percent of females who are 60 inches tall will weigh between 90.341 ($94.932 - 4.591 = 90.341$) and 99.523 ($94.932 + 4.591 = 99.523$) pounds.

Drawing Conclusions

Conclusions from regression analyses indicate (a) whether or not a significant prediction equation was obtained, (b) the direction of the relationship, and (c) the equation itself. Multiple regression is generally much more powerful than simple linear regression. Compare our two examples.

With multiple regression, you must also consider the **significance** level of each **independent variable**. In the example above, the **significance** level of both **independent variables** is less than .001.

Phrasing Results That Are Significant

In our example, we obtained an *R* Square of .993 and a regression equation of $\text{WEIGHT}' = 47.138 - 39.133(\text{SEX}) + 2.101(\text{HEIGHT})$. The ANOVA resulted in $F = 981.202$

with 2 and 13 degrees of freedom. F is significant at the less than .001 level. Thus, we could state the following in a results section:

A multiple linear regression was calculated to predict participants' weight based on their height and sex. A significant regression equation was found ($F(2,13) = 981.202, p < .001$), with an R^2 of .993. Participants' predicted weight is equal to $47.138 - 39.133(\text{SEX}) + 2.101(\text{HEIGHT})$, where SEX is coded as 1 = Male, 2 = Female, and HEIGHT is measured in inches. Participants increased 2.101 pounds for each inch of height, and males weighed 39.133 pounds more than females. Both SEX and HEIGHT were significant predictors.

The conclusion states the direction (increase), strength (.993), value (981.20), degrees of freedom (2,13), and significance level ($< .001$) of the regression. In addition, a statement of the equation itself is included. Because there are multiple independent variables, we have noted whether or not each is significant.

Phrasing Results That Are Not Significant

The screenshot displays the IBM SPSS Statistics Viewer interface. The main window shows the following regression output:

Regression

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	WORK, TRAINING ^b		Enter

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

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.991 ^a	.924	.773	2.50000

a. Predictors: (Constant), WORK, TRAINING

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	76.500	2	38.250	6.120	.275 ^b
	Residual	6.250	1	6.250		
	Total	82.750	3			

a. Dependent Variable: GRADE
b. Predictors: (Constant), WORK, TRAINING

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	78.750	2.165		36.373	.017
	TRAINING	7.500	2.500	.824	3.000	.205
	WORK	-4.500	2.500	-.495	-1.800	.323

a. Dependent Variable: GRADE

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If the ANOVA does not find a significant relationship, the *Sig.* section of the output will be greater than .05, and the regression equation will not be significant. A results section for the output shown here (based on *SAMPLE.sav*) might include the following statement:

A multiple linear regression was calculated predicting participants' grades based on whether or not they received training and the amount they work. The regression equation was not significant ($F(2,1) = 6.12, p > .05$) with an R^2 of .924. Neither training nor working is a significant predictor of grades.

Note that for results that are not significant, the ANOVA results and R^2 results are given, but the regression equation is not.

Practice Exercise

Use Practice Dataset 2 in Appendix B. Determine the regression equation for predicting salary based on education, years of service, and sex. Which variables are significant predictors? If you believe that men were paid more than women, what would you conclude after conducting this analysis?

Chapter 6

Basic Parametric Inferential Statistics and t Tests

Parametric inferential statistical procedures allow you to draw inferences about populations based on samples of those populations. To make these inferences, you must be able to make certain assumptions about the shape of the distributions of the population samples.

Section 6.1 Review of Basic Hypothesis Testing

The Null Hypothesis

In hypothesis testing, we create two hypotheses that are **mutually exclusive** (i.e., both cannot be true at the same time) and **all inclusive** (i.e., one of them must be true). We refer to those two hypotheses as the **null hypothesis** and the **alternative hypothesis**. The **null hypothesis** generally states that any difference we observe is caused by random error. The **alternative hypothesis** generally states that any difference we observe is caused by a systematic difference between groups.

Type I and Type II Errors

All hypothesis testing attempts to draw conclusions about the real world based on the results of a test (a statistical test, in this case). There are four possible combinations of results.

REAL WORLD

		Null Hypothesis True	Null Hypothesis False
TEST RESULTS	Reject Null Hypothesis	Type I Error	No Error
	Fail to Reject Null Hypothesis	No Error	Type II Error

Two of the possible results are correct test results. The other two results are errors. A **Type I error** occurs when we reject a **null hypothesis** that is, in fact, true, while a **Type II error** occurs when we fail to reject a **null hypothesis** that is, in fact, false.

Significance tests determine the probability of making a **Type I error** (often called *alpha* $<\alpha>$, *Sig.*, or *p*). In other words, after performing a series of calculations, we obtain a probability of obtaining a value as far from expected as we got assuming the **null hypothesis** is true. If there is a low probability, such as 5 or less in 100 (.05), by convention, we reject the **null hypothesis**. In other words, we typically use the .05 level (or less) as the maximum **Type I error** rate we are willing to accept.

When there is a low probability of a **Type I error**, such as .05, we can state that the **significance** test has led us to “reject the **null hypothesis**.” This is synonymous with saying that a difference is “statistically significant.” For instance, on a reading test, suppose you found that a random sample of girls from a school district scored higher than a random sample of boys. This result may have been obtained merely because the chance errors associated with random sampling created the observed difference (this is what the **null hypothesis** asserts). If there is a sufficiently low probability that random errors were the cause (as determined by a **significance** test), we can state that the difference between boys and girls is statistically significant.

Significance Levels Versus Critical Values

Most statistics textbooks present hypothesis testing by using the concept of a critical value. With such an approach, we obtain a value for a test statistic and compare it to a

critical value we look up in a table. If the obtained value is larger than the critical value, we reject the **null hypothesis** and conclude that we have found a significant difference (or relationship). If the obtained value is less than the critical value, we fail to reject the **null hypothesis** and conclude that there is not a significant difference.

The critical-value approach is well suited to hand calculations. Tables that give critical values for alpha levels of .001, .01, .05, and so on, can be created. It is not practical to create a table for every possible alpha level.

On the other hand, SPSS can determine the exact alpha level associated with any value of a test statistic. Thus, looking up a critical value in a table is not necessary. This, however, does change the basic procedure for determining whether or not to reject the **null hypothesis**.

The section of SPSS output labeled *Sig.* (sometimes *p* or *alpha α') indicates the likelihood of making a **Type I error** if we reject the **null hypothesis**. A value of .05 or less indicates that we should reject the **null hypothesis** (assuming an alpha level of .05). A value greater than .05 indicates that we should fail to reject the **null hypothesis**.*

In other words, when using SPSS, we normally reject the **null hypothesis** if the output value under *Sig.* is equal to or smaller than .05, and we fail to reject the **null hypothesis** if the output value is larger than .05.

One-Tailed Versus Two-Tailed Tests

SPSS output generally includes a two-tailed alpha level (normally labeled *Sig.* in the output). A two-tailed hypothesis attempts to determine whether any difference (either positive or negative) exists. Thus, you have an opportunity to make a **Type I error** on either of the two tails of the normal distribution.

A one-tailed test examines a difference in a specific direction. Thus, we can make a **Type I error** on only one side (tail) of the distribution. If we have a one-tailed hypothesis, but our SPSS output gives a two-tailed **significance** result, we can take the **significance** level in the output and divide it by two. Thus, if our difference is in the right direction, and if our output indicates a **significance** level of .084 (two-tailed), but we have a one-tailed hypothesis, we can report a **significance** level of .042 (one-tailed).

Phrasing Results

Results of hypothesis testing can be stated in different ways, depending on the conventions specified by your institution. The following examples illustrate some of these differences.

Degrees of Freedom

Sometimes the degrees of freedom are given in parentheses immediately after the symbol representing the test, as in this example:

$$t(3) = 7.00, p < .01$$

Other times, the degrees of freedom are given within the statement of results, as in this example:

$$t = 7.00, df = 3, p < .01$$

Significance Level

When you obtain results that are significant, they can be described in different ways. For instance, if you obtained a **significance** level of .006 on a *t* test, you could describe it in any of the following three ways:

$$\begin{aligned}t(3) &= 7.00, p < .05 \\t(3) &= 7.00, p < .01 \\t(3) &= 7.00, p = .006\end{aligned}$$

Notice that because the exact probability is .006, both .05 and .01 are also correct. There are also various ways of describing results that are not significant. For instance, if you obtained a **significance** level of .505, any of the following three statements could be used:

$$\begin{aligned}t(2) &= 0.805, ns \\t(2) &= 0.805, p > .05 \\t(2) &= 0.805, p = .505\end{aligned}$$

Statement of Results

Sometimes the results will be stated in terms of the **null hypothesis**, as in the following example:

The null hypothesis was rejected ($t = 7.00, df = 3, p = .006$).

Other times, the results are stated in terms of their level of **significance**, as in the following example:

A statistically significant difference was found: $t(3) = 7.00, p < .01$.

Statistical Symbols

Generally, statistical symbols are presented in *italics*. Prior to the widespread use of computers and desktop publishing, statistical symbols were underlined. Underlining is a signal to a printer that the underlined text should be set in italics. Institutions vary on their requirements for student work, so you are advised to consult your instructor about this.

Section 6.2 Single-Sample *t* Test

Description

The single-sample *t* test compares the **mean** of a single sample to a known population mean. It is useful for determining if the current set of data has changed from a long-term value (e.g., comparing the current year's temperatures to a historical average to determine if global warming is occurring).

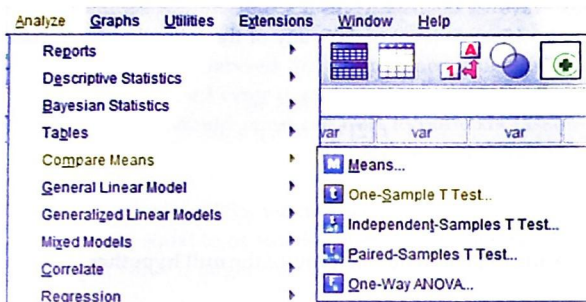
Assumptions

The distributions from which the scores are taken should be normally distributed. However, the *t* test is **robust** and can handle violations of the assumption of a **normal distribution**. The **dependent variable** must be measured on an **interval or ratio scale**.

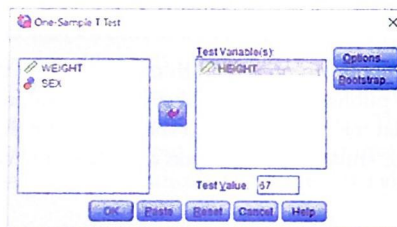
SPSS Data Format

The SPSS data file for the single-sample t test requires a single variable in SPSS. That variable represents the set of scores in the sample that we will compare to the population mean.

Running the Command



This example uses the HEIGHT.sav data file created in Chapter 4. The one sample (also called “single-sample”) t test is located in the *Compare Means* submenu, under the *Analyze* menu.



The dialog box for the single-sample t test requires that we transfer the variable representing the current set of scores to the *Test Variable(s)* section. We must also enter the population average in the *Test Value* blank. The example presented here is testing the variable HEIGHT against a population mean of 67. In other words, we are testing whether the sample came from a population with a mean of 67. Click *OK* to run the analysis.

Reading the Output

The output for the single-sample t test consists of two sections. The first section lists the sample variable and some basic **descriptive statistics** (N , mean, standard deviation, and standard error).

The screenshot shows the IBM SPSS Statistics Viewer interface. The main window displays the results of a T-Test for the variable HEIGHT. The output is organized into two main sections: One-Sample Statistics and One-Sample Test.

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
HEIGHT	16	66.9375	3.90672	.97668

One-Sample Test

Test Value = 67

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
HEIGHT	-.064	15	.950	-.06250	-2.1442	2.0192

The status bar at the bottom indicates "IBM SPSS Statistics Processor is ready" and "Unicode:ON | H: 104, W: 653 pt".

The second section of output contains the results of the t test. The example presented above indicates a t value of $-.064$, with 15 degrees of freedom and a significance level of $.95$. The **mean** difference of $-.0625$ is the difference between the sample average (66.9375) and the population average we entered in the **dialog box** to conduct the test (67).

Drawing Conclusions

The assumption when conducting a t test is that the means are equal. Therefore, a significant result indicates that the sample **mean** is not equivalent to the population **mean** (hence the term "significantly different"). A result that is not significant means that there is not a significant difference between the means. It does not mean that they are equal. Refer to your statistics text for the section on failure to reject the **null hypothesis**.

Phrasing Results That Are Significant

The above example did not find a significant difference between the population **mean** and the sample **mean**. If, however, we had used a population **mean** of 64 instead of 67, we would have obtained the following output:

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
HEIGHT	16	66.9375	3.90672	.97668

One-Sample Test

Test Value = 64

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
HEIGHT	3.008	15	.009	2.93750	8.558	50.192

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 104, W: 646 pt

In this case, we could state the following:

A single-sample t test that compared the mean height of the sample to a population value of 64 was conducted. A significant difference was found ($t(15) = 3.008, p = .009$). The sample mean of 66.9375 ($sd = 3.907$) was significantly greater than the population mean.

Phrasing Results That Are Not Significant

In our first example, the significance level was greater than .05. Thus, we would state the following:

A single-sample t test that compared the mean height of the sample to a population value of 67 was conducted. No significant difference was found ($t(15) = -.064, p = .95$). The sample mean of 66.9375 ($sd = 3.907$) was not significantly greater than the population mean.

Practice Exercise

The mean salary in the United States is a hypothetical average of \$25,000. Determine if the mean salary of the participants in Practice Dataset 2 in Appendix B is significantly greater than this value. Note that this is a one-tailed hypothesis.

Section 6.3 Independent-Samples t Test

Description

The independent-samples t test compares the means of two independent samples. Samples are independent if there is no relationship between them (generally meaning each participant provides data for only one sample).

Assumptions

The two groups being compared should be independent of each other. Observations are independent when information about one is unrelated to the other. Normally, this means that one group of participants provides data for one sample and a different group of participants provides data for the other sample (and individuals in one group are not matched with individuals in the other group). One way to accomplish this is through using **random assignment** to form two groups.

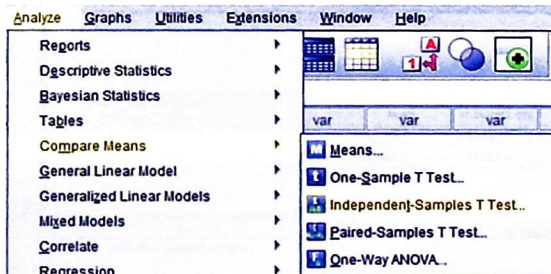
The scores should be normally distributed, but the t test is **robust** and can handle violations of the assumption of a **normal distribution**. The two samples should, however, have the same variance.

The **dependent variable** must be measured on an **interval or ratio scale**. The **independent variable** should have only two **discrete** levels.

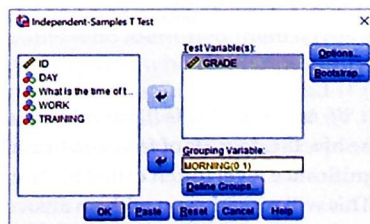
SPSS Data Format

The SPSS data file for the independent t test requires two variables. One variable, the **grouping variable**, represents the value of the **independent variable**. The **grouping variable** should have two distinct values (e.g., 0 for a control group and 1 for an experimental group). The second variable represents the **dependent variable**, such as scores on a test.

Conducting an Independent-Samples t Test

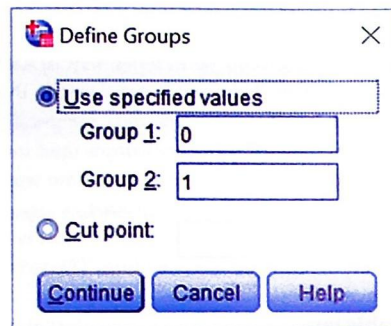


For our example, we will use the SAMPLE.sav data file. Click *Analyze*, then *Compare Means*, then *Independent-Samples T Test*. This will bring up the main dialog box. Transfer the **dependent variable(s)** into the *Test Variable(s)* blank. For our example, we will use the variable GRADE.



Transfer the **independent variable** into the *Grouping Variable* section. For our example, we will use the variable MORNING.

Next, click *Define Groups* and enter the values of the two **levels** of the **independent variable** (0 for nonmorning and 1 for morning). Independent t tests are capable of comparing only two levels at a time. Click *Continue*, then click *OK* to run the analysis.



Output from the Independent-Samples t Test

The output will have a section labeled “Group Statistics.” This section provides the basic descriptive statistics for the dependent variable(s) for each value of the independent variable. Next, there will be a section with the results of the t test. The output should look like the image below.

Group Statistics

Are you a morning person?	N	Mean	Std. Deviation	Std. Error Mean
GRADE No	2	82.5000	3.53553	2.50000
GRADE Yes	2	78.0000	7.07107	5.00000

Independent Samples Test

		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
GRADE	Equal variances assumed			505	2	505	4.50000	5.59017	-19.55256	28.55256
	Equal variances not assumed			805	1.471	530	4.50000	5.59017	-30.09261	39.09261

The columns labeled t , df , and $Sig. (2-tailed)$ provide the standard answer for the t test. They provide the value of t , the degrees of freedom (number of participants minus 2, in this case), and the significance level (often called p). Normally, we use the “Equal variances assumed” row. This will provide you with an answer equivalent to what you would calculate by hand.

Drawing Conclusions

Recall from the previous section that the t test assumes an equality of means. Therefore, a significant result indicates that the means are not equivalent. When drawing conclusions about a t test, you must state the direction of the difference (i.e., which

mean was larger than the other). You should also include information about the value of t , the degrees of freedom, the significance level, the means, and standard deviations for the two groups.

Phrasing Results That Are Significant

For a significant t test (e.g., the output below), you might state the following:

An independent-samples t test comparing the mean scores of the experimental and control groups found a significant difference between the means of the two groups ($t(5) = 2.835, p < .05$). The mean of the experimental group was significantly lower ($M = 33.333, sd = 2.08$) than the mean of the control group ($M = 41.000, sd = 4.24$).

The screenshot shows the IBM SPSS Statistics Viewer interface. The main window displays the results of a T-Test. The 'Group Statistics' table shows the mean and standard deviation for two groups. The 'Independent Samples Test' table shows the results of Levene's Test for Equality of Variances and the t-test for Equality of Means.

group	N	Mean	Std. Deviation	Std. Error Mean
score 1.00	6	6.1667	1.16905	.47726
2.00	6	3.1667	1.16905	.47726

	Levene's Test for Equality of Variances		t-test for Equality of Means				95% Confidence Interval of the Difference			
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper	
score										
	Equal variances assumed	.000	1.000	4.445	10	.001	3.00000	.67495	1.49612	4.50388
	Equal variances not assumed			4.445	10.000	.001	3.00000	.67495	1.49612	4.50388

Phrasing Results That Are Not Significant

In our example at the start of this section, we compared the scores of the morning people to the scores of the nonmorning people. We did not find a significant difference, so we could state the following:

An independent-samples t test was calculated comparing the mean score of participants who identified themselves as morning people to the mean score of participants who did not identify themselves as morning people. No significant difference was found ($t(2) = 0.805, p > .05$). The mean of the morning people ($M = 78.00, sd = 7.07$) was not significantly different from the mean of nonmorning people ($M = 82.50, sd = 3.54$).

Practice Exercise

Use Practice Dataset 1 in Appendix B to solve this problem. We believe that young individuals have lower mathematics skills than older individuals. We would test this hypothesis by comparing participants 25 or younger (the "young" group) with participants 26 or older (the "old" group). Hint: You may need to create a new variable that represents each age group. See Chapter 2 for help.

Section 6.4 Paired-Samples t Test

Description

The paired-samples t test (also called a dependent t test) compares the **means** of two scores from related samples. For instance, comparing a pretest and a posttest score for a group of participants would require a paired-samples t test.

Assumptions

The paired-samples t test assumes that **both variables** are at the **interval** or **ratio** levels and are normally distributed. The two variables should also be measured with the same scale.

SPSS Data Format

Two variables in the SPSS data file are required. These variables should represent two measurements from each participant.

Running the Command

We will create a new data file containing five variables: PRETEST, MIDTERM, FINAL, INSTRUCT, and REQUIRED. INSTRUCT represents three different instructors for a course. REQUIRED represents whether the course was required or was an elective (0 = elective, 1 = required). The other three variables represent exam scores (100 being the highest score possible).

PRETEST	MIDTERM	FINAL	INSTRUCT	REQUIRED
56	64	69	1	0
79	91	86	1	0
68	77	81	1	0
59	69	71	1	1
64	77	75	1	1
74	88	86	1	1
73	85	86	1	1
47	64	69	2	0
78	98	100	2	0
61	77	85	2	0
68	86	93	2	1
64	77	87	2	1
53	67	76	2	1
71	85	95	2	1
61	79	97	3	0
57	77	89	3	0
49	65	83	3	0
71	93	100	3	1
61	83	94	3	1
58	75	92	3	1
58	74	92	3	1

Enter the data and save them as GRADES.sav. You can check your data entry by computing a mean for each instructor using the *Means* command. (See Chapter 3 for more information.) Use INSTRUCT as the independent variable, and enter PRETEST, MIDTERM, and FINAL as your dependent variables.

Means

Case Processing Summary

	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
pretest * instruct	21	100.0%	0	0.0%	21	100.0%
midterm * instruct	21	100.0%	0	0.0%	21	100.0%
final * instruct	21	100.0%	0	0.0%	21	100.0%

Report

instruct		pretest	midterm	final
1.00	Mean	67.5714	78.7143	79.1429
	N	7	7	7
	Std. Deviation	8.38366	9.94509	7.42582
2.00	Mean	63.1429	79.1429	86.4286
	N	7	7	7
	Std. Deviation	10.60548	11.71080	10.92180
3.00	Mean	59.2857	78.0000	92.4286
	N	7	7	7
	Std. Deviation	6.55017	8.62168	5.50325
Total	Mean	63.3333	78.6190	86.0000
	N	21	21	21
	Std. Deviation	8.92935	9.66166	9.61249

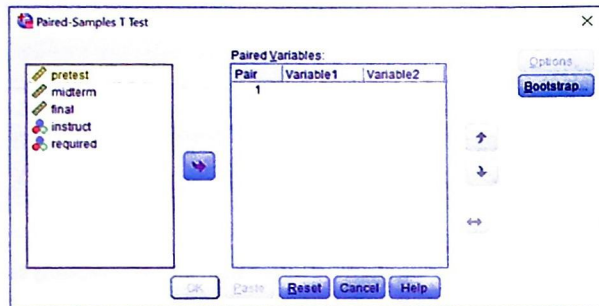
IBM SPSS Statistics Processor is ready Unicode.ON



Once you have entered the data, conduct a paired-samples *t* test comparing pretest scores and final scores.

Analyze Graphs Utilities Extensions Window Help

- Regots
- Descriptive Statistics
- Bayesian Statistics
- Tables
- Compare Means
 - Means...
 - One-Sample T Test..
 - Independent-Samples T Test..
 - Paired-Samples T Test..
 - One-Way ANOVA..
- General Linear Model
- Generalized Linear Models
- Mixed Models
- Correlate
- Regression

Click *Analyze*, then *Compare Means*, then *Paired-Samples T Test*. This will bring up the main dialog box.



You must select pairs of variables to compare. Click on PRETEST, then click the  button. Click on FINAL, then click the  button. (Alternatively, you can double-click or control-click them.) The variables will be moved into the *Paired Variables* area. Click OK to conduct the test.

Reading the Output

The output for the paired-samples *t* test consists of three components. The first part gives you basic descriptive statistics for the pair of variables. The PRETEST average was 63.3, with a standard deviation of 8.93. The FINAL average was 86.00, with a standard deviation of 9.61.

T-Test

Paired Samples Statistics

	Mean	N	Std. Deviation	Std. Error Mean
Pair 1 pretest	63.3333	21	8.92935	1.94854
final	86.0000	21	9.61249	2.09762

Paired Samples Correlations

	N	Correlation	Sig.
Pair 1 pretest & final	21	.509	.019

Paired Samples Test

Paired Differences

	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
				Lower	Upper			
Pair 1 pretest - final	-22.66667	9.21050	2.00990	-26.85924	-18.47410	-11.278	20	.000

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 64, W: 677 pt.

The second part of the output is a Pearson correlation coefficient for the pair of variables. Within the third part of the output (labeled *Paired Samples Test*), the section called *Paired Differences* contains information about the differences between the two variables. You may have learned in your statistics class that the paired-samples *t* test is essentially a single-sample *t* test calculated on the differences between the scores. The final three columns contain the value of *t*, the degrees of freedom, and the **significance** level. In the example presented here, we obtained a *t* of -11.278 , with 20 degrees of freedom, and a **significance** level of less than $.000$ (which is actually just $< .001$).

Drawing Conclusions

Paired-samples *t* tests determine whether or not two means are significantly different from each other. Significant values indicate that the two means are different (technically, that the samples come from populations with different means). Values that are not significant indicate that the scores are not significantly different.

Phrasing Results That Are Significant

When stating the results of a paired-samples *t* test, you should give the value of *t*, the degrees of freedom, and the **significance** level. You should also give the **mean** and **standard deviation** for each variable, as well as a statement of results that indicates whether you conducted a one- or two-tailed test. Our example above was significant, so we could state the following:

A paired-samples *t* test was calculated to compare the mean pretest score to the mean final exam score. The mean on the pretest was 63.33 ($sd = 8.93$), and the mean on the final was 86.00 ($sd = 9.61$). A significant increase from pretest to final was found ($t(20) = -11.278, p < .001$).

Phrasing Results That Are Not Significant

If the **significance** level had been greater than $.05$ (or greater than $.10$, if you were conducting a one-tailed test), the result would not have been significant. If you select only the students who have instructor #1 and conduct a test to compare midterm and final scores you will get the output here.

The screenshot shows the IBM SPSS Statistics Viewer window with the following output:

T-Test

Paired Samples Statistics

	Mean	N	Std. Deviation	Std. Error Mean
Pair 1: midterm	78.7143	7	9.94509	3.75889
final	79.1429	7	7.42582	2.80670

Paired Samples Correlations

	N	Correlation	Sig.
Pair 1: midterm & final	7	.955	.001

Paired Samples Test

Paired Differences

	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference			t	df	Sig. (2-tailed)
				Lower	Upper				
Pair 1: midterm - final	-4.2857	3.59894	1.36027	-3.75704	2.89989	-3.15	6	.763	

For this analysis, we could state the following:

A paired-samples t test was calculated to compare midterm and final exam scores for students had instructor one. The mean on the midterm was 78.71 ($sd = 9.95$), and the mean on the final was 79.14 ($sd = 7.43$). No significant difference from pretest to final was found ($t(6) = -.315, p > .05$).

Practice Exercise

Use the same GRADES.sav data file, and compute a paired-samples t test to determine if scores increased from midterm to final.

Chapter 7

ANOVA Models

Section 7.1 ANOVA Models

Analysis of variance (ANOVA) is a procedure that determines the proportion of variability attributed to each of several components. It is one of the most useful and adaptable statistical techniques available.

In general ANOVA procedures in SPSS produce what is called a **Source Table** in which each row represents a source of variability and the columns represent what we know about the variability attributable to each source. In the simplest case total variability is split into that attributable to differences between the groups and the variability attributable to differences within the groups.

Normally there is a column called SS (Sum of Squares), one for df (Degrees of Freedom), one for MS (Mean Squares), and then F – which is the actual answer.

Section 7.2 One-Way ANOVA

Description

The one-way ANOVA compares the means of two or more groups of participants that vary on a single **independent variable** (thus, the one-way designation). When we have three groups, we could use a *t* test to determine differences between the groups, but we would have to conduct three *t* tests (Group 1 compared to Group 2, Group 1 compared to Group 3, and Group 2 compared to Group 3). When we conduct multiple *t* tests, we inflate the **Type I error** rate and increase our chance of drawing an inappropriate conclusion. ANOVA compensates for these multiple comparisons and gives us a single answer that tells us if any of the groups is different from any of the other groups.

Assumptions

The one-way ANOVA requires a single **dependent variable** and a single **independent variable**. Which group participants belong to is determined by the value of the **independent variable**. Groups should be independent of each other. If our participants belong to more than one group each, we will have to conduct a repeated-measures ANOVA. If we have more than one **independent variable**, we should conduct a factorial ANOVA.

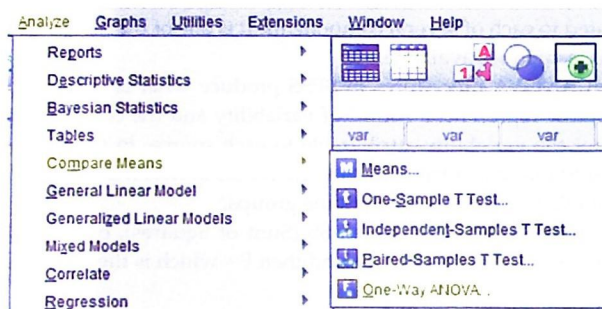
ANOVA also assumes that the **dependent variable** is at the **interval** or **ratio** level and is normally distributed, and that the variances of the **dependent variable** for each level of the **independent variable** are equal.

SPSS Data Format

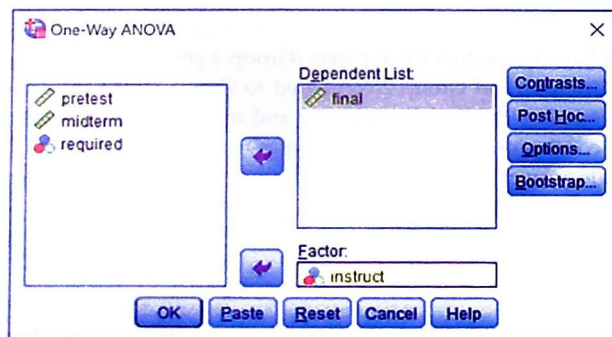
Two variables are required in the SPSS data file. One variable serves as the **dependent variable** and the other as the **independent variable**. Each participant should provide only one score for the **dependent variable**.

Running the Command

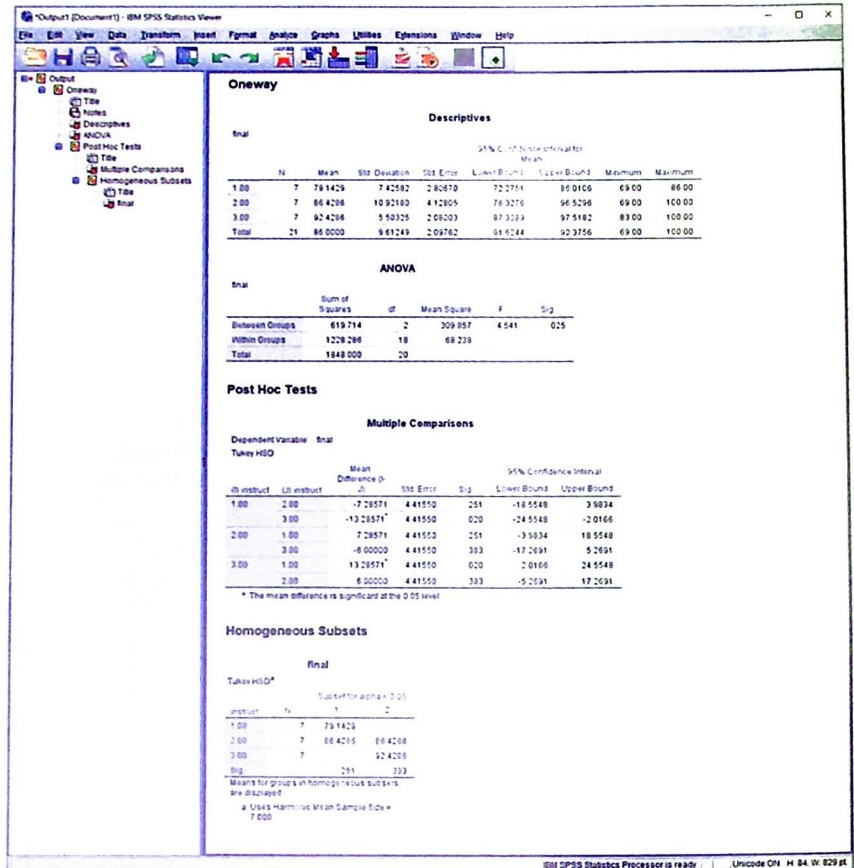
For this example, we will use the GRADES.sav data file we created in the previous section.



For you to conduct a one-way ANOVA, click *Analyze*, then *Compare Means*, then *One-Way ANOVA*. This will bring up the main dialog box for the *One-Way ANOVA* command.



You should place the **independent variable** in the *Factor* box. For our example, INSTRUCT represents three different instructors, and it will be used as our **independent variable**. Our **dependent variable** will be FINAL. This test will allow us to determine if the instructor has any effect on final grades in the course.



The next section of the output is the ANOVA source table. This is where the various components of the variance have been listed, along with their relative sizes. For a one-way ANOVA, there are two components to the variance: Between Groups (which represents the differences due to our independent variable) and Within Groups (which represents differences within each level of our independent variable). For our example, the Between Groups variance represents differences due to different instructors. The Within Groups variance represents individual differences among students.

The primary answer is F . F is a ratio of explained variance to unexplained variance. Consult a statistics text for more information on how it is determined. The F has two different degrees of freedom, one for Between Groups (in this case, 2 is the number of levels of our independent variable $<3-1>$), and another for Within Groups (18 is the number of participants minus the number of levels of our independent variable $<21-3>$).

The next part of the output consists of the results of our Tukey's HSD post-hoc comparison. This table presents us with every possible combination of levels of our independent variable. The first row represents Instructor 1 compared to Instructor 2. Next is Instructor 1 compared to Instructor 3. Next is Instructor 2 compared to Instructor 1. (Note that this is redundant with the first row.) Next is Instructor 2 compared to Instructor 3, and so on.

The column labeled $Sig.$ represents the Type I error (p) rate for the simple (2-level) comparison in that row. In our example above, Instructor 1 is significantly different from Instructor 3, but Instructor 1 is not significantly different from Instructor 2, and Instructor 2 is not significantly different from Instructor 3.

Drawing Conclusions

Drawing conclusions for ANOVA requires that we indicate the value of F , the degrees of freedom, and the significance level. A significant ANOVA should be followed by the results of a post-hoc analysis and a verbal statement of the results.

Phrasing Results That Are Significant

In the preceding example, we could state the following:

We computed a one-way ANOVA comparing the final exam scores of participants who took a course from one of three different instructors. A significant difference was found among the instructors ($F(2,18) = 4.541, p < .05$). Tukey's HSD was used to determine the nature of the differences between the instructors. This analysis revealed that students who had Instructor 1 scored lower ($M = 79.14, sd = 7.43$) than students who had Instructor 3 ($M = 92.43, sd = 5.50$). Students who had Instructor 2 ($M = 86.43, sd = 10.92$) were not significantly different from either of the other two groups.

Phrasing Results That Are Not Significant

If we had conducted the analysis using PRETEST as our dependent variable instead of FINAL, we would have received the following output:

The screenshot displays the SPSS Statistics Viewer interface with the following output sections:

Oneway Descriptives

pretest	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	7	67.5714	8.38366	3.16872	59.8178	75.3250	56.00	79.00
2.00	7	63.1429	10.60548	4.00849	53.3344	72.9513	47.00	78.00
3.00	7	59.2857	6.55017	2.47573	53.2278	65.3436	49.00	71.00
Total	21	63.3333	8.92935	1.94854	59.2687	67.3979	47.00	79.00

ANOVA

pretest	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	240.667	2	120.333	1.600	.229
Within Groups	1354.000	18	75.222		
Total	1594.667	20			

Post Hoc Tests

Multiple Comparisons

Dependent Variable: pretest

Tukey HSD

(i) instruct	(j) instruct	Mean Difference (i-j)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	4.42857	4.63595	.613	-7.4031	16.2603
1.00	3.00	8.28571	4.63595	.202	-3.5460	20.1174
2.00	1.00	-4.42857	4.63595	.613	-16.2603	7.4031
2.00	3.00	3.85714	4.63595	.689	-7.9746	15.6889
3.00	1.00	-8.28571	4.63595	.202	-20.1174	3.5460
3.00	2.00	-3.85714	4.63595	.689	-15.6889	7.9746

Homogeneous Subsets

pretest

Tukey HSD^a

instruct	N	Subset for alpha = 0.05	
		1	2
3.00	7	59.2857	
2.00	7	63.1429	
1.00	7	67.5714	
			202
			Sig.

Means for groups in homogeneous subsets are displayed.

^a Uses Harmonic Mean Sample Size = 7.000

The ANOVA was not significant, so there is no need to refer to the Multiple Comparisons table. Given this result, we may state the following:

The pretest means of students who took a course from three different instructors were compared using a one-way ANOVA. No significant difference was found ($F(2,18) = 1.60, p > .05$). The students from the three different classes did not differ significantly at the start of the term. Students who had Instructor 1 had a mean score of 67.57 ($sd = 8.38$). Students who had Instructor 2 had a mean score of 63.14 ($sd = 10.61$). Students who had Instructor 3 had a mean score of 59.29 ($sd = 6.55$).

Practice Exercise

Using Practice Dataset 1 in Appendix B, determine if the average math scores of single, married, and divorced participants are significantly different. Write a statement of results.

Section 7.3 Factorial ANOVA

Description

The factorial ANOVA is one in which there is more than one **independent variable**. A 2×2 ANOVA, for instance, has two **independent variables**, each with two **levels**. A $3 \times 2 \times 2$ ANOVA has three **independent variables**. One has three **levels**, and the other two have two **levels**. Factorial ANOVA is very powerful because it allows us to assess the effects of each **independent variable**, plus the effects of the **interaction**.

Interactions occur when the effect of one variable impacts the effect of another variable on the **dependent variable**. For instance, there is an **interaction** between soap and water, influencing their effects on their cleaning ability. In this instance, the effect of soap and water together is greater than their individual effects added together.

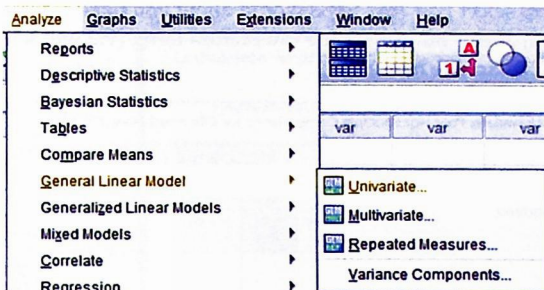
Assumptions

Factorial ANOVA requires all of the assumptions of one-way ANOVA (i.e., the **dependent variable** must be at the **interval** or **ratio** level and normally distributed). In addition, the **independent variables** should be independent of each other.

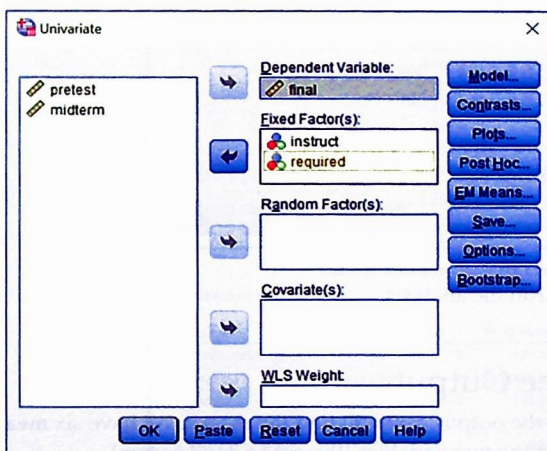
SPSS Data Format

SPSS requires one variable for the **dependent variable** and one variable for each **independent variable**. If we have *any* **independent variable** that is represented as multiple variables (e.g., PRETEST and POSTTEST), we must use the repeated-measures ANOVA.

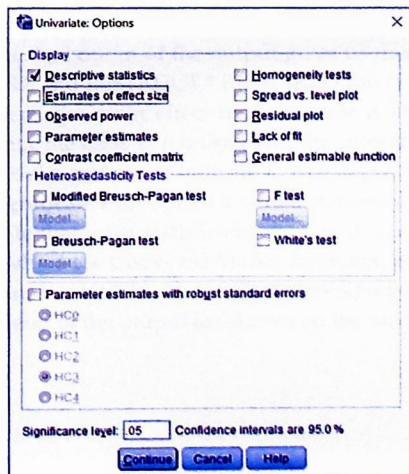
Running the Command



This example uses the GRADES.sav data file from earlier in this chapter. Click *Analyze*, then *General Linear Model*, then *Univariate*.

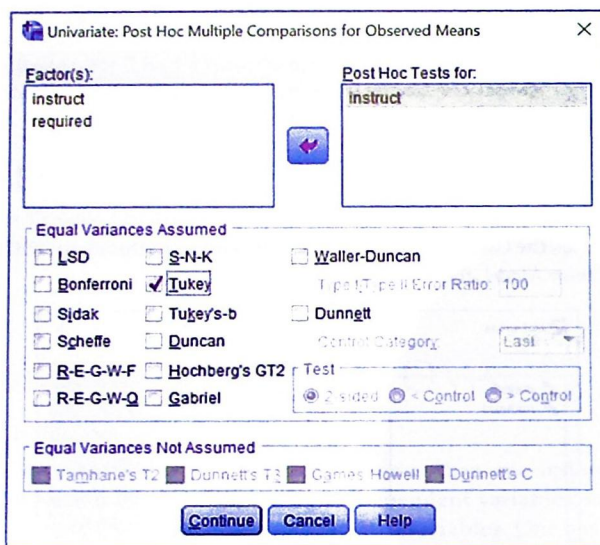


This will bring up the main dialog box for Univariate ANOVA. Select the dependent variable and place it in the *Dependent Variable* blank (use FINAL for this example). Select one of your independent variables (INSTRUCT in this case), and place it in the *Fixed Factor(s)* box. Place the second independent variable (REQUIRED) in the *Fixed Factor(s)* box. Having defined the analysis, now click *Options*.



When the Options dialog box comes up, click *Descriptive statistics*. This will provide you with **means** for each main effect and **interaction** term. Click *Continue*.

If you were to select *Post Hoc*, SPSS would allow you to elect to run post-hoc analyses for any main effects but not for the **interaction** term. (We will select Tukey's HSD for the INSTRUCT variable here.)



Click *OK* to run the analysis.

Reading the Output

In the middle of the output, you will find the means. We have six **means** representing the interaction of the two variables (this was a 3×2 design).

Participants who had Instructor 1 (for whom the class was not required) had a **mean** final exam score of 79.67. Students who had Instructor 1 (for whom it was required) had a **mean** final exam score of 79.50, and so on.

The example we just ran is called a two-way ANOVA. This is because we had two **independent variables**. With a two-way ANOVA, we get three answers: a main effect for INSTRUCT, a main effect for REQUIRED, and an **interaction** result for INSTRUCT*REQUIRED.

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Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Univariate Analysis of Variance
 - Title
 - Notes
 - Between-Subjects Factors
 - Descriptive Statistics
 - Tests of Between-Subjects Effects
 - Post Hoc Tests
 - Title
 - instruct
 - Title
 - Multiple Comparisons
 - Homogeneous Subsets
 - Title
 - final

Univariate Analysis of Variance

Between-Subjects Factors

	Value Label	N
instruct	1.00	7
	2.00	7
	3.00	7
required	.00 No	9
	1.00 Yes	12

Descriptive Statistics

Dependent Variable: final

instruct	required	Mean	Std. Deviation	N
1.00	No	78.6667	8.73689	3
	Yes	79.5000	7.68115	4
	Total	79.1429	7.42582	7
2.00	No	84.6667	15.50269	3
	Yes	87.7500	8.53913	4
	Total	86.4286	10.92180	7
3.00	No	89.6667	7.02377	3
	Yes	94.5000	3.78594	4
	Total	92.4286	5.50325	7
Total	No	84.3333	10.68878	9
	Yes	87.2500	8.99621	12
	Total	86.0000	9.61249	21

Tests of Between-Subjects Effects

Dependent Variable: final

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	677.250 ^a	5	135.450	1.735	.187
Intercept	151410.036	1	151410.036	1939.911	.000
instruct	581.214	2	290.607	3.723	.049
required	43.750	1	43.750	.561	.466
instruct * required	13.786	2	6.893	.088	.916
Error	1170.750	15	78.050		
Total	157164.000	21			
Corrected Total	1848.000	20			

a. R Squared = .366 (Adjusted R Squared = .155)

The source table at the bottom of the output gives us these three answers (in the INSTRUCT, REQUIRED, and INSTRUCT * REQUIRED rows).

In the example here, the main effect for Instructor is significant, but the main effect for whether or not the class is required and the interaction are not significant. In the statements of results, you must indicate *F*, two degrees of freedom (effect and residual/error), the **significance** level, and a verbal statement for each of the answers (three in this case). Note that most statistics books give a much simpler version of an ANOVA source table where the Corrected Model, Intercept, and Corrected Total rows are not included. Because one of the main effects was significant, there are also post-hoc results at the very end of the output (as shown on the next page).

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IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Univariate Analysis of Variance
 - Title
 - Notes
 - Between-Subjects Factors
 - Descriptive Statistics
 - Tests of Between-Subjects Effects
 - Post Hoc Tests
 - Title
 - instruct
 - Title
 - Multiple Comparisons
 - Homogeneous Subsets
 - Title
 - final

Post Hoc Tests

instruct

Multiple Comparisons

Dependent Variable: final

Tukey HSD

		Mean Difference (I-J)		Sig.	95% Confidence Interval	
(i) instruct	(j) instruct	Mean	Std. Error		Lower Bound	Upper Bound
1.00	2.00	-7.2857	4.72229	.300	-19.5517	4.9803
	3.00	-13.2857*	4.72229	.033	-25.5517	-1.0197
2.00	1.00	7.2857	4.72229	.300	-4.9803	19.5517
	3.00	-6.0000	4.72229	.432	-18.2660	6.2660
3.00	1.00	13.2857*	4.72229	.033	1.0197	25.5517
	2.00	6.0000	4.72229	.432	-6.2660	18.2660

Based on observed means
The error term is Mean Square(Error) = 78.050
* The mean difference is significant at the .05 level.

Homogeneous Subsets

final

Tukey HSD^{a,b}

instruct	N	Subset	
		1	2
1.00	7	79.1429	
2.00	7	86.4286	86.4286
3.00	7		92.4286
Sig.		.300	.432

Means for groups in homogeneous subsets are displayed
Based on observed means
The error term is Mean Square(Error) = 78.050
a. Uses Harmonic Mean Sample Size = 7.000.
b. Alpha = .05

Phrasing Results That Are Significant

For the example we just ran we could say:

A 3 (instructor) \times 2 (required course) between-subjects factorial ANOVA was calculated comparing the final exam scores for participants who had one of three instructors and who took the course either as a required course or as an elective. A significant main effect for instructor was found ($F(2,15) = 3.723, p < .05$). Students who had Instructor 1 had lower final exam scores ($M = 79.14, sd = 7.43$) than students who had Instructor 3 ($M = 92.43, sd = 5.50$). Students who had Instructor 2 ($M = 86.43, sd = 10.92$) were not significantly different from either of the other two groups. A significant main effect for whether or not the course was required was not found ($F(1,15) = .561, p > .05$). Students who took the course because it was required did not do significantly better ($M = 87.25, sd = 9.61$) than students who took the course as an elective ($M = 84.33, sd = 10.69$). The interaction was not significant ($F(2,15) = 0.088, p > .05$). The effect of the instructor was not influenced by whether or not the students took the course because it was required.

Phrasing Results That Are Not Significant

If you repeat the analysis using MIDTERM as the **Dependent Variable** you will receive the following non-significant output:

The screenshot displays the SPSS Univariate Analysis of Variance output for the dependent variable 'midterm'. The output is organized into three main sections: Between-Subjects Factors, Descriptive Statistics, and Tests of Between-Subjects Effects.

Between-Subjects Factors

	Value Label	N
instruct	1.00	7
	2.00	7
	3.00	7
required	.00 No	9
	1.00 Yes	12

Descriptive Statistics

Dependent Variable: midterm

instruct	required	Mean	Std. Deviation	N
1.00	No	77.3333	13.50309	3
	Yes	79.7500	8.53913	4
	Total	78.7143	9.94509	7
2.00	No	79.6667	17.15615	3
	Yes	78.7500	8.80814	4
	Total	79.1429	11.71080	7
3.00	No	73.6667	7.57188	3
	Yes	81.2500	8.80814	4
	Total	78.0000	8.62168	7
Total	No	76.8889	11.84741	9
	Yes	79.9167	7.95965	12
	Total	78.6190	9.66166	21

Tests of Between-Subjects Effects

Dependent Variable: midterm

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	114.702 ^a	5	22.940	.196	.959
Intercept	126452.480	1	126452.480	1082.487	.000
instruct	10.698	2	5.349	.046	.955
required	47.147	1	47.147	.404	.535
instruct * required	62.889	2	31.444	.269	.768
Error	1752.250	15	116.817		
Total	131667.000	21			
Corrected Total	1866.952	20			

a. R Squared = .061 (Adjusted R Squared = -.251)

A 3 (instructor) \times 2 (required course) between-subjects factorial ANOVA was calculated comparing the midterm exam scores for participants who had one of three instructors and who took the course as a required course or as an elective. The main effect for instructor was not significant ($F(2,15) = .046, p > .05$). The main effect for whether or not it was a required course was also not significant ($F(1,15) = .404, p > .05$). Finally, the interaction was not significant ($F(2,15) = .269, p > .05$). Thus, it appears that neither the instructor nor whether or not the course is required has any significant effect on midterm exam scores.

Practice Exercise

Using Practice Dataset 2 in Appendix B, determine if salaries are influenced by sex, job classification, or an interaction between sex and job classification. Write a statement of results.

Section 7.4 Repeated-Measures ANOVA

Description

Repeated-measures ANOVA extends the basic ANOVA procedure to a within-subjects independent variable (when participants provide data for more than one level of an independent variable). It functions like a paired-samples t test when more than two levels are being compared.

Assumptions

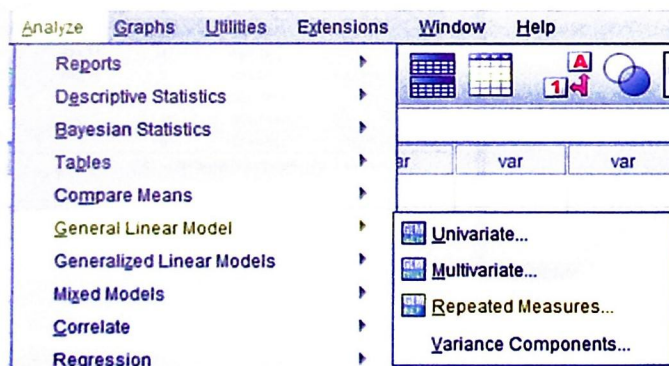
The dependent variable should be normally distributed and measured on an interval or ratio scale. Multiple measurements of the dependent variable should be from the same (or related) participants.

SPSS Data Format

At least three variables are required. Each variable in the SPSS data file should represent a single dependent variable at a single level of the independent variable. Thus, an analysis of a design with four levels of an independent variable would require four variables in the SPSS data file.

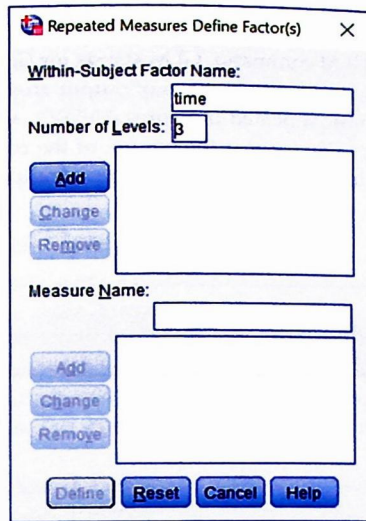
If any variable represents a between-subjects effect, use the *Repeated Measures ANOVA* command instead.

Running the Command



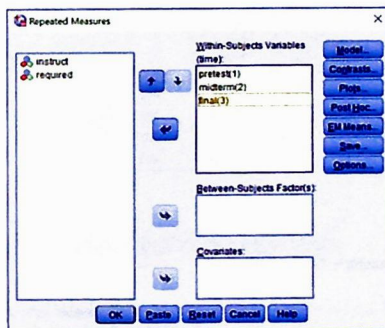
This example uses the GRADES.sav sample dataset. Recall that GRADES.sav includes three sets of grades—PRETEST, MIDTERM, and FINAL—that represent three different times during the semester. This allows us to analyze the effects of time on the test performance of our sample population (hence the within-groups comparison). Click *Analyze*, then *General Linear Model*, then *Repeated Measures*.

Note that this procedure requires an optional module. If you do not have this command, you do not have the necessary module installed. This procedure is NOT included in the SPSS Statistics GradPack Base.

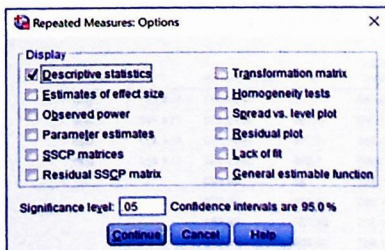


After selecting the command, you will be presented with the Repeated Measures Define Factor(s) dialog box. This is where you identify the Within-Subject Factor (we will call it TIME). Enter 3 for the Number of Levels (three exams) and click *Add*.

If we had more than one independent variable that had repeated measures, we could enter its name and click *Add*. Now click *Define*.



You will be presented with the Repeated Measures dialog box. Transfer PRETEST, MIDTERM, and FINAL to the *Within-Subjects Variables* section. The variable names should be ordered according to when they occurred in time (i.e., the values of the independent variable that they represent).



Click *Options*, and the dialog box here will appear. Select *Descriptive statistics*, SPSS will calculate the relevant means. Click *CONTINUE* to close the dialog box and *OK* to run the command.

Reading the Output

This procedure uses the *GLM* command. *GLM* stands for *General Linear Model*. It is a very powerful command, and many sections of output are beyond the scope of this book. However, for the basic repeated-measures ANOVA, we are interested only in the *Tests of Within-Subjects Effects* (near the bottom of the output shown here). Note that the SPSS output will include many other sections of output, which you can ignore at this point.

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

time	Variable
1	pretest
2	midterm
3	final

Descriptive Statistics

	Mean	Std. Deviation	N
pretest	63.3333	8.92935	21
midterm	76.6190	9.66166	21
final	86.0000	9.61249	21

Multivariate Tests^a

Effect		Value	F	Hypothesis df	Error df	Sig.
time	Pillai's Trace	.941	151.569 ^b	2.000	19.000	.000
	Wilks' Lambda	.059	151.569 ^b	2.000	19.000	.000
	Hotelling's Trace	15.955	151.569 ^b	2.000	19.000	.000
	Roy's Largest Root	15.955	151.569 ^b	2.000	19.000	.000

^a Design: Intercept
Within Subjects Design: time

^b Exact statistic

Mauchly's Test of Sphericity^a

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Greenhouse-Geisser	Huynh-Feldt	Lower-bound
time	.336	20.718	2	.000	.601	.618	.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: time

^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

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	5613.365	2	2806.683	114.407	.000
	Greenhouse-Geisser	5613.365	1.202	4670.114	114.407	.000
	Huynh-Feldt	5613.365	1.236	4540.162	114.407	.000
	Lower-bound	5613.365	1.000	5613.365	114.407	.000
Error(time)	Sphericity Assumed	981.302	40	24.533		
	Greenhouse-Geisser	981.302	24.040	40.820		
	Huynh-Feldt	981.302	24.728	39.684		
	Lower-bound	981.302	20.000	49.065		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

IBM SPSS Statistics Processor is ready | Unicode ON | H: 22, W: 872 pt

The *Tests of Within-Subjects Effects* output should look very similar to the output from the other ANOVA commands. In the example on the previous page, the effect of TIME has an F value of 114.407 with 2 and 40 degrees of freedom (we use the line for *Sphericity Assumed*). It is significant at less than the .001 level. When describing these results, we should indicate the type of test, F value, degrees of freedom, and **significance level**.

Phrasing Results That Are Significant

Because the ANOVA results were significant, we need to conduct some sort of post-hoc analysis. One of the main limitations of SPSS is the difficulty in performing post-hoc analyses for within-subjects factors. With SPSS, the easiest solution to this problem is to conduct **protected dependent t tests** with repeated-measures ANOVA. There are more powerful (and more appropriate) post-hoc analyses, but SPSS will not compute them for us. For more information, consult your instructor or a more advanced statistics text.

To conduct the protected t tests, we will compare PRETEST to MIDTERM, MIDTERM to FINAL, and PRETEST to FINAL, using paired-samples t tests. Because we are conducting three tests and, therefore, inflating our **Type I error rate**, we will use a significance level of .017 (.05/3) instead of .05. Note that to conduct this analysis, we will need to use the paired-samples t test command and enter all three pairs.



The three comparisons each had a **significance level** of less than .017, so we can conclude that the scores improved from pretest to midterm and again from midterm to final. To generate the **descriptive statistics**, we have to run the *Descriptives* command for each variable.

The screenshot shows the IBM SPSS Statistics Viewer interface. The main window displays the results of a T-Test analysis. The left sidebar shows the 'Output' tree with 'T-Test' expanded to show 'Paired Samples Statistics', 'Paired Samples Correlations', and 'Paired Samples Test'. The main area contains three tables: 'Paired Samples Statistics', 'Paired Samples Correlations', and 'Paired Samples Test'.

T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	pretest	63.3333	21	8.92935	1.94854
	midterm	78.6190	21	9.66166	2.10935
Pair 2	pretest	63.3333	21	8.92935	1.94854
	final	86.0000	21	9.61249	2.09762
Pair 3	midterm	78.6190	21	9.66166	2.10935
	final	86.0000	21	9.61249	2.09762

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	pretest & midterm	21	.912	.000
Pair 2	pretest & final	21	.509	.019
Pair 3	midterm & final	21	.749	.000

Paired Samples Test

Paired Differences

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	pretest - midterm	-15.28571	3.96412	.65504	-17.09016	-13.48127	-17.670	20	.000
Pair 2	pretest - final	-22.66667	9.21050	2.00990	-26.85924	-18.47410	-11.278	20	.000
Pair 3	midterm - final	-7.38095	6.82991	1.49041	-10.48989	-4.27202	-4.952	20	.000

Because the results of our example were significant, we could state the following:

A one-way repeated-measures ANOVA was calculated comparing the exam scores of participants at three different times: pretest, midterm, and final. A significant effect was found ($F(2,40) = 114.407, p < .001$). Follow-up protected t tests revealed that scores increased significantly from pretest ($M = 63.33, sd = 8.93$) to midterm ($M = 78.62, sd = 9.66$), and again from midterm to final ($M = 86.00, sd = 9.62$).

Phrasing Results That Are Not Significant

With results that are not significant, we could state the following (the output here comes from the TIME.sav datafile in Appendix C):

A one-way repeated-measures ANOVA was calculated comparing the scores of participants at three different times: before, during, and after. No significant effect was found ($F(2,10) = .044, p > .05$). No significant difference exists among before ($M = 3.50, sd = 1.05$), during ($M = 3.67, sd = 1.03$), and after ($M = 3.67, sd = 1.03$).

IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- General Linear Model
 - Table
 - Notes
 - Within-Subjects Factors
 - Descriptive Statistics
 - Multivariate Tests
 - Mauchly's Test of Sphericity
 - Tests of Within-Subjects
 - Tests of Within-Subjects
 - Tests of Between-Subjects

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

time	Dependent Variable
1	before
2	during
3	after

Descriptive Statistics

	Mean	Std. Deviation	N
before	3.5000	1.04881	6
during	3.6667	1.03280	6
after	3.6667	1.03280	6

Multivariate Tests^a

Effect	Value	F	Hypothesis df	Error df	Sig.
time					
Pillai's Trace	.024	.049 ^b	2.000	4.000	.953
Wilks' Lambda	.976	.049 ^b	2.000	4.000	.953
Hotelling's Trace	.024	.049 ^b	2.000	4.000	.953
Roy's Largest Root	.024	.049 ^b	2.000	4.000	.953

a. Design: Intercept
Within Subjects Design: time

b. Exact statistic

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
time	.694	1.454	2	.481	.765	1.000	.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: time

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.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
time					
Sphericity Assumed	.111	2	.056	.044	.957
Greenhouse-Geisser	.111	1.531	.073	.044	.922
Huynh-Feldt	.111	2.000	.056	.044	.957
Lower-bound	.111	1.000	.111	.044	.842
Error(time)					
Sphericity Assumed	12.556	10	1.256		
Greenhouse-Geisser	12.556	7.654	1.640		
Huynh-Feldt	12.556	10.000	1.256		
Lower-bound	12.556	5.000	2.511		

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Practice Exercise

Use Practice Dataset 3 in Appendix B. Determine if the anxiety level of participants changed over time (regardless of which treatment they received) using a one-way repeated-measures ANOVA and protected dependent t tests. Write a statement of results.

Section 7.5 Mixed-Design ANOVA

Description

The mixed-design ANOVA (sometimes called a split-plot design) tests the effects of more than one **independent variable**. At least one of the **independent variables** must be within-subjects (repeated measures). At least one of the **independent variables** must be between-subjects.

Assumptions

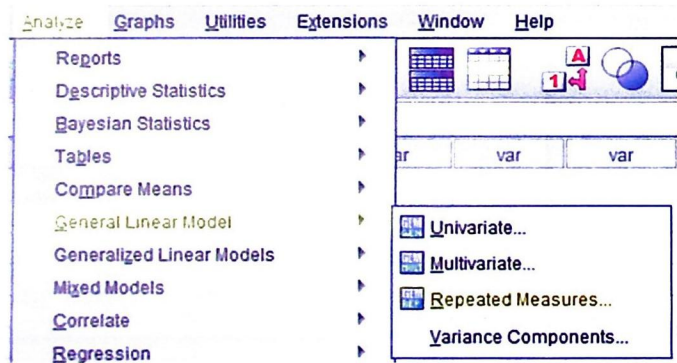
The **dependent variable** should be normally distributed and measured on an interval or ratio scale.

SPSS Data Format

The **dependent variable** should be represented as one variable (one column) for each level of the within-subjects **independent variables**. Another variable (column) should be present in the data file for each between-subjects variable. Thus, a 2×2 mixed-design ANOVA would require three columns: two representing the **dependent variable** (one at each level) and one representing the between-subjects **independent variable**.

Running the Command

The *General Linear Model* command runs the *Repeated Measures ANOVA* command. Click *Analyze*, then *General Linear Model*, then *Repeated Measures*.

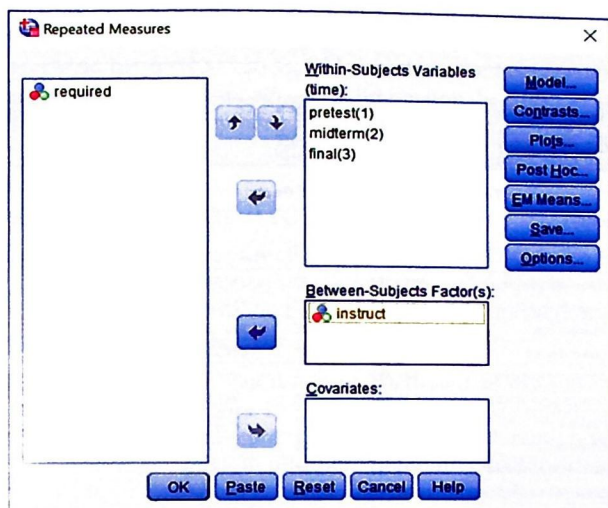


Note that this procedure requires an optional module. If you do not have this command, you do not have the necessary module installed. This procedure is NOT included in the SPSS Statistics GradPack Base.

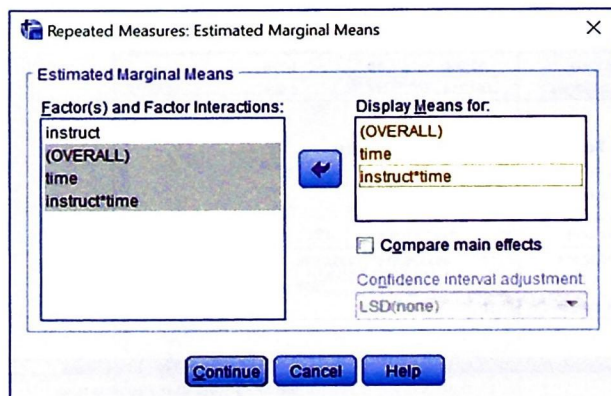
The *Repeated Measures* command should be used if any of the **independent variables** are repeated measures (within-subjects).

This example also uses the GRADES.sav data file. Enter PRE-TEST, MIDTERM, and FINAL in the *Within-Subjects Variables* block. (See the *Repeated Measures ANOVA* command in Section 7.4 for an explanation.) This example is a 3×3 mixed-design. There are two **independent variables** (TIME and INSTRUCT), each with three levels. We previously entered the information for TIME in the *Repeated Measures Define Factors* dialog box.

We need to transfer INSTRUCT into the *Between-Subjects Factor(s)* block.



The *Descriptive statistics* option we used for one-way repeated-measures ANOVA will not work here because it only provides descriptive statistics for repeated-measures variables. Instead, we will select *EM Means* and move each of our main effects and the interaction over.



Click *OK* to run the command.

Reading the Output

As with the standard *Repeated Measures* command, the *GLM* procedure provides a significant amount of output we will not use. For a mixed-design ANOVA, we are

interested in two sections. The first is *Tests of Within-Subjects Effects*, and the second is *Tests of Between-Subjects Effects*. Both of those are shown here.

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	5613.365	2	2806.683	723.194	.000
	Greenhouse-Geisser	5613.365	1.233	4551.266	723.194	.000
	Huynh-Feldt	5613.365	1.425	3937.856	723.194	.000
	Lower-bound	5613.365	1.000	5613.365	723.194	.000
time * instruct	Sphericity Assumed	841.587	4	210.397	54.213	.000
	Greenhouse-Geisser	841.587	2.467	341.176	54.213	.000
	Huynh-Feldt	841.587	2.851	295.193	54.213	.000
	Lower-bound	841.587	2.000	420.794	54.213	.000
Error(time)	Sphericity Assumed	139.714	36	3.881		
	Greenhouse-Geisser	139.714	22.201	6.293		
	Huynh-Feldt	139.714	25.659	5.445		
	Lower-bound	139.714	18.000	7.762		

Tests of Within-Subjects Contrasts

Source	time	Type III Sum of Squares	df	Mean Square	F	Sig.
time	Linear	5394.667	1	5394.667	3034.500	.000
	Quadratic	218.698	1	218.698	36.546	.000
time * instruct	Linear	816.333	2	408.167	229.594	.000
	Quadratic	25.254	2	12.627	2.110	.150
Error(time)	Linear	32.000	18	1.778		
	Quadratic	107.714	18	5.984		

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	363736.016	1	363736.016	1520.898	.000
instruct	23.460	2	11.730	.049	.952
Error	4304.857	18	239.159		

This section gives two of the three answers we need (the main effect for TIME and the **interaction** result for TIME \times INSTRUCTOR). The second section of output is *Tests of Between-Subjects Effects* (sample output is above). Here, we get the answers that do not contain any within-subjects effects. For our example, we get the main effect for INSTRUCT. Both of these sections must be combined to produce the full answer for our analysis.

If we obtain significant effects, we must perform some sort of post-hoc analysis. Again, this is one of the limitations of SPSS. No easy way to perform the appropriate

post-hoc test for repeated-measures (within-subjects) factors is available (You can have it conduct post-hoc tests on between-subjects factors). Ask your instructor for assistance with this.

When describing the results, you should include F , the degrees of freedom, and the **significance** level for each main effect and **interaction**. In addition, some **descriptive statistics** must be included (either give means or include a figure).

Phrasing Results That Are Significant

There are (at least) three answers for all mixed-design ANOVAs. See Section 7.3 on factorial ANOVA for more details about how to interpret and phrase the results. For the above example, we could state the following in the results section (note that this assumes that appropriate post-hoc tests have been conducted):

A 3×3 mixed-design ANOVA was calculated to examine the effects of the instructor (Instructors 1, 2, and 3) and time (pretest, midterm, and final) on scores. A significant time \times instructor interaction was present ($F(4,36) = 52.213, p < .001$). In addition, the main effect for time was significant ($F(2,36) = 723.194, p < .001$). The main effect for instructor was not significant ($F(2,18) = .049, p > .05$).

With significant **interactions**, it is often helpful to provide a graph with the **descriptive statistics**. By selecting the *Plots* option in the main **dialog box**, you can make graphs of the **interaction** like the one on the next page. **Interactions** add considerable complexity to the interpretation of statistical results. Consult a research methods text or ask your instructor for more help with **interactions**.

Repeated Measures: Profile Plots

Factors:

instruct
time

Horizontal Axis:

Separate Lines:

Separate Plots:

Plots:

instruct*time

Chart Type:

Line Chart
 Bar Chart

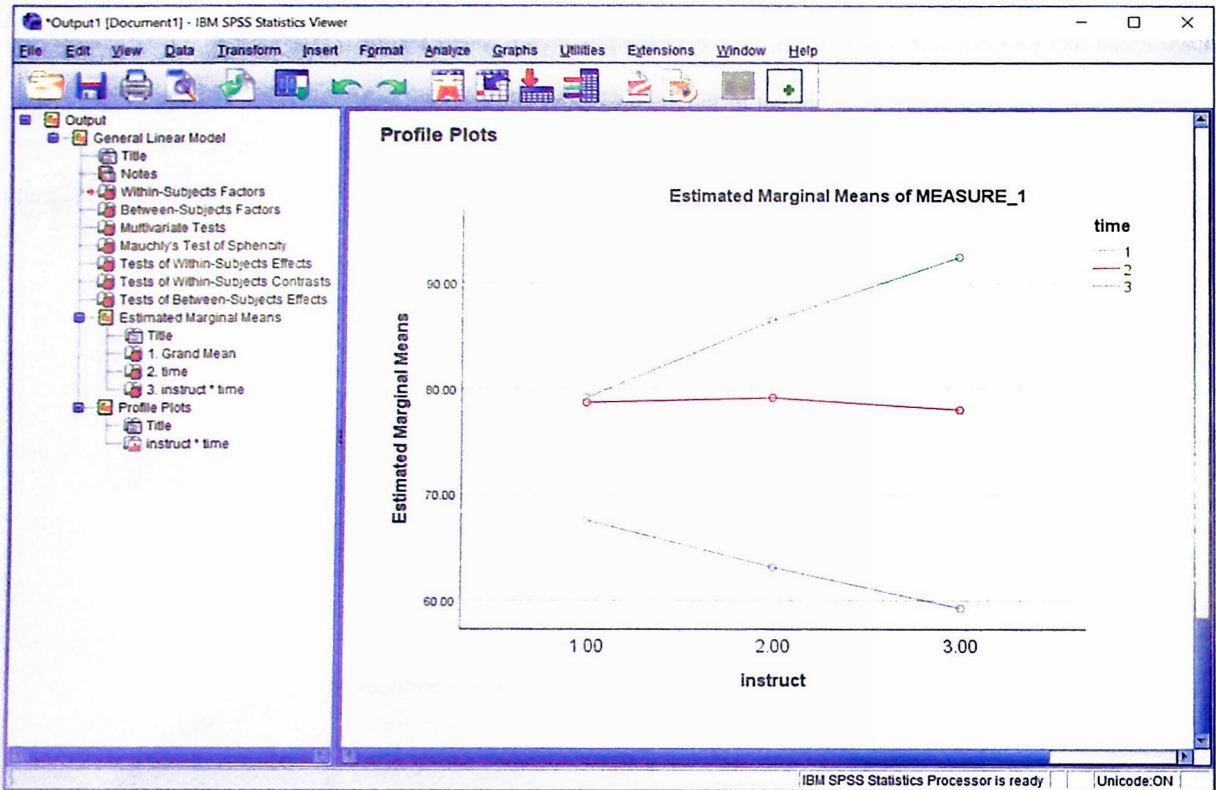
Error Bars

Include Error bars

Confidence Interval (95.0%)
 Standard Error Multiplier: 2

Include reference line for grand mean
 Y axis starts at 0

Continue Cancel Help



Phrasing Results That Are Not Significant

If our results had not been significant (this output is from TIME.sav in Appendix C), we could have stated the following:

A 3×2 mixed-design ANOVA was calculated to examine the effects of the group (1 or 2) and time (before, during, after) on scores. No significant main effects or interactions were found. The time \times group interaction ($F(2,8) = .809, p > .05$), the main effect for time ($F(2,8) = .043, p > .05$), and the main effect for group ($F(1,4) = .250, p > .05$) were not significant. Scores were not influenced by either time or group.

SPSS Statistics Viewer window showing the output of a General Linear Model. The output is divided into three sections: Tests of Within-Subjects Effects, Tests of Within-Subjects Contrasts, and Tests of Between-Subjects Effects.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	.111	2	.056	.043	.959
	Greenhouse-Geisser	.111	1.571	.071	.043	.928
	Huynh-Feldt	.111	2.000	.056	.043	.959
	Lower-bound	.111	1.000	.111	.043	.847
time * group	Sphericity Assumed	2.111	2	1.056	.809	.479
	Greenhouse-Geisser	2.111	1.571	1.344	.809	.458
	Huynh-Feldt	2.111	2.000	1.056	.809	.479
	Lower-bound	2.111	1.000	2.111	.809	.419
Error(time)	Sphericity Assumed	10.444	8	1.306		
	Greenhouse-Geisser	10.444	6.282	1.663		
	Huynh-Feldt	10.444	8.000	1.306		
	Lower-bound	10.444	4.000	2.611		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	time	Type III Sum of Squares	df	Mean Square	F	Sig.
time	Linear	.083	1	.083	125	.742
	Quadratic	.028	1	.028	.014	.911
time * group	Linear	.750	1	.750	1.125	.349
	Quadratic	1.361	1	1.361	700	.450
Error(time)	Linear	2.667	4	.667		
	Quadratic	7.778	4	1.944		

Tests of Between-Subjects Effects

Measure: MEASURE_1
Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	234.722	1	234.722	422.500	.000
group	1.389	1	1.389	2.500	.189
Error	2.222	4	.556		

Practice Exercise

Use Practice Dataset 3 in Appendix B. Determine if anxiety levels changed over time for each of the treatment (CONDITION) types. How did time change anxiety levels for each treatment? Write a statement of results.

Section 7.6 Analysis of Covariance

Description

Analysis of covariance (ANCOVA) allows you to remove the effect of a known **covariate**. In this way, it becomes a statistical method of control. With methodological controls (e.g., **random assignment**), **internal validity** is gained. When such methodological controls are not possible, statistical controls can be used.

ANCOVA can be performed by using the *GLM* command if you have repeated-measures factors. Because the *GLM* command is not included in the Base Statistics module, it is not included here.

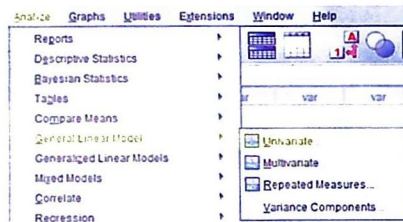
Assumptions

ANCOVA requires that the **covariate** be significantly correlated with the **dependent variable**. The **dependent variable** and the **covariate** should be at the **interval or ratio levels**. In addition, both should be normally distributed.

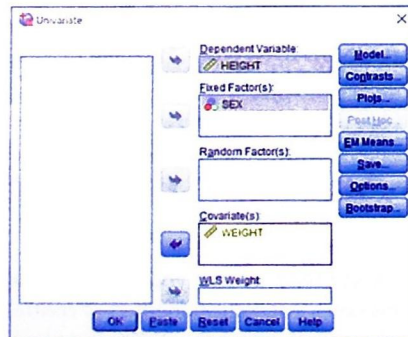
SPSS Data Format

The SPSS data file must contain one variable for each **independent variable**, one variable representing the **dependent variable**, and at least one **covariate**.

Running the Command



The *Factorial ANOVA* command is used to run ANCOVA. To run it, click *Analyze*, then *General Linear Model*, then *Univariate*. Follow the directions discussed for factorial ANOVA, using the HEIGHT.sav sample data file. Place the variable HEIGHT as your *Dependent Variable*. Enter SEX as your *Fixed Factor*, then WEIGHT as the *Covariate*. This last step determines the difference between regular factorial ANOVA and ANCOVA. To obtain descriptive statistics check *Descriptive statistics* under *Options*. Click *OK* to run the ANCOVA.



Reading the Output

The output consists of one main source table (shown on the next page). This table gives you the main effects and **interactions** you would have received with a normal factorial ANOVA. In addition, there is a row for each **covariate**. In our example, we have one

main effect (SEX) and one covariate (WEIGHT). Normally, we examine the covariate line only to confirm that the covariate is significantly related to the dependent variable.

Univariate Analysis of Variance

Between-Subjects Factors

	Value Label	N
SEX	1.00 Male	8
	2.00 Female	8

Descriptive Statistics

Dependent Variable: HEIGHT

SEX	Mean	Std. Deviation	N
Male	69.3750	3.70087	8
Female	64.5000	2.32993	8
Total	66.9375	3.90672	16

Tests of Between-Subjects Effects

Dependent Variable: HEIGHT

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	215.027 ^a	2	107.513	100.476	.000
Intercept	5.580	1	5.580	5.215	.040
WEIGHT	119.964	1	119.964	112.112	.000
SEX	66.367	1	66.367	62.023	.000
Error	13.911	13	1.070		
Total	71919.000	16			
Corrected Total	228.938	15			

a. R Squared = .939 (Adjusted R Squared = .930)

Drawing Conclusions

This sample analysis was performed to determine if males and females differ in height after weight is accounted for. We know that weight is related to height. Rather than match participants or use methodological controls, we can statistically remove the effect of weight.

When giving the results of ANCOVA, we must give F , degrees of freedom, and significance levels for all main effects, interactions, and covariates. If main effects or interactions are significant, post-hoc tests must be conducted. Descriptive statistics (mean and standard deviation) for each level of the independent variable should also be given.

Phrasing Results That Are Significant

The previous example obtained a significant result, so we could state the following:

A one-way between-subjects ANCOVA was calculated to examine the effect of sex on height, covarying out the effect of weight. Weight was significantly related to height ($F(1,13) = 112.11, p < .001$). The main effect for sex was significant ($F(1,13) = 62.02, p < .001$), with males significantly taller ($M = 69.38, sd = 3.70$) than females ($M = 64.50, sd = 2.33$).

Phrasing Results That Are Not Significant

If the **covariate** is not significant, we need to repeat the analysis without including the **covariate** (i.e., run a normal ANOVA).

For ANCOVA results that are not significant (but the covariate is significant), you could state the following (this output is obtained from the GRADES.sav datafile running an ANCOVA on FINAL grades, covarying out PRETEST to see if REQUIRED has an effect):

A one-way between-subjects ANCOVA was calculated to examine the effect of being a required course on final exam scores, covarying out the pretest scores. Pretest scores were significantly related to final exam scores ($F(1,18) = 5.891, p < .05$). The main effect for being a required course was not significant ($F(1,18) = .142, p > .05$).

IBM SPSS Statistics Processor is ready | Unicode ON | H: 22, W: 1025 pt

Univariate Analysis of Variance					
Between-Subjects Factors					
	Value Label	N			
required	00 No	9			
	1.00 Yes	12			

Tests of Between-Subjects Effects					
Dependent Variable: final					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	489.643 ^a	2	244.822	3.235	.063
Intercept	1037.571	1	1037.571	13.739	.002
pretest	444.693	1	444.693	5.891	.026
required	10.720	1	10.720	.142	.711
Error	1359.357	18	75.520		
Total	157164.000	21			
Corrected Total	1648.000	20			

^a R Squared = .264 (Adjusted R Squared = .187)

Practice Exercise

Using Practice Dataset 2 in Appendix B, determine if salaries are different for males and females. Repeat the analysis, statistically controlling for years of service. Write a statement of results for each. Compare and contrast your two answers.

Section 7.7 Multivariate Analysis of Variance (MANOVA)

Description

Multivariate tests are those that involve more than one **dependent variable**. While it is possible to conduct several univariate tests (one for each **dependent variable**), this causes **Type I error** inflation. Multivariate tests look at all **dependent variables** at

once, in much the same way that ANOVA looks at all levels of an **independent variable** at once.

Assumptions

MANOVA assumes that you have multiple **dependent variables** that are related to each other. Each **dependent variable** should be normally distributed and measured on an **interval** or **ratio scale**.

SPSS Data Format

The SPSS data file should have a variable for each **dependent variable**. One additional variable is required for each between-subjects **independent variable**. It is also possible to do a MANCOVA, a repeated-measures MANOVA, and a repeated-measures MANCOVA. These extensions require additional variables in the data file.

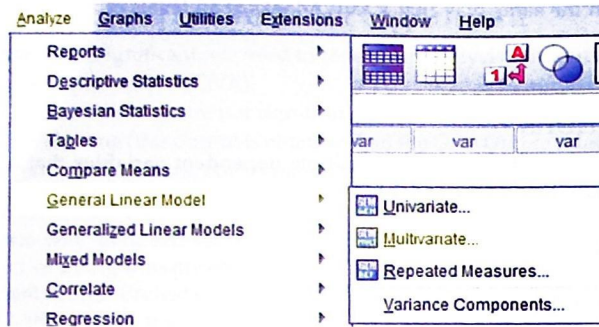
Running the Command

Note that this procedure requires an optional module. If you do not have this command, you do not have the necessary module installed. This procedure is NOT included in the SPSS Statistics GradPack Base.

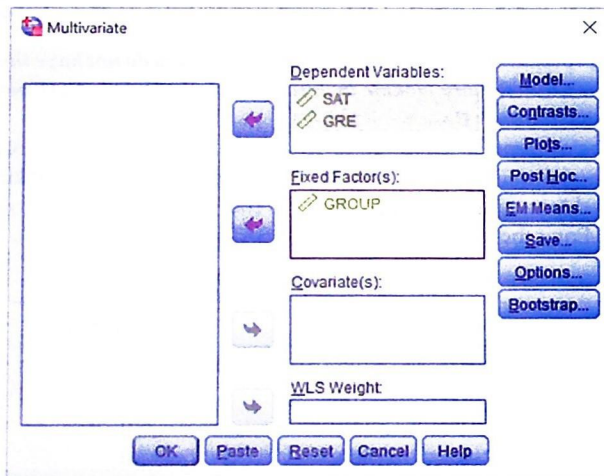
The data below represent SAT and GRE scores for 18 participants. Six participants received no special training, six received short-term training before taking the tests, and six received long-term training. GROUP is coded 0 = no training, 1 = short-term, 2 = long-term. Enter the data and save them as SAT.sav.

SAT	GRE	GROUP
580	600	0
520	520	0
500	510	0
410	400	0
650	630	0
480	480	0
500	490	1
640	650	1
500	480	1
500	510	1
580	570	1
490	500	1
520	520	2
620	630	2
550	560	2
500	510	2
540	560	2
600	600	2

Locate the *Multivariate* command by clicking *Analyze*, then *General Linear Model*, then *Multivariate*.



This will bring up the main dialog box. Enter the **dependent variables** (SAT and GRE, in this case) in the *Dependent Variable(s)* box. Enter the **independent variable** (GROUP, in this case) in the *Fixed Factor(s)* box. Click OK to run the command.



Reading the Output

We are interested in two primary sections of output. The first one gives the results of the multivariate tests. The section labeled GROUP is the one we want. This tells us whether GROUP had an effect on any of our **dependent variables**. Four different types of multivariate test results are given. The most widely used is *Wilks' Lambda*. Thus, the answer for the MANOVA is a *Lambda* of .828, with 4 and 28 degrees of freedom. That value is not significant.

The second section of output we want gives the results of the Between-Subjects univariate tests (ANOVAs) for each **dependent variable**.

Output [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- General Linear Model
 - Title
 - Notes
 - Between-Subjects Factors
 - Multivariate Tests
 - Tests of Between-Subjects Effects

General Linear Model

Between-Subjects Factors

	Value	Label	N
GROUP	.00	No Training	6
	1.00	Short Term	6
	2.00	Long Term	6

Multivariate Tests^a

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.988	569.187 ^b	2 000	14 000	.000
	Wilks' Lambda	.012	569.187 ^b	2 000	14 000	.000
	Hotelling's Trace	81.312	569.187 ^b	2 000	14 000	.000
	Roy's Largest Root	81.312	569.187 ^b	2 000	14 000	.000
GROUP	Pillai's Trace	.174	.713	4 000	30 000	.590
	Wilks' Lambda	.828	.693 ^b	4 000	28 000	.603
	Hotelling's Trace	.206	.669	4 000	26 000	.619
	Roy's Largest Root	.196	1.469 ^c	2 000	15 000	.261

a. Design: Intercept + GROUP
 b. Exact statistic
 c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	SAT	3077.778 ^a	2	1538.889	360	.703
	GRE	5200.000 ^b	2	2600.000	587	.568
Intercept	SAT	5205688.889	1	5205688.889	1219.448	.000
	GRE	5248800.000	1	5248800.000	1185.723	.000
GROUP	SAT	3077.778	2	1538.889	360	.703
	GRE	5200.000	2	2600.000	587	.568
Error	SAT	64033.333	15	4268.889		
	GRE	66400.000	15	4426.667		
Total	SAT	5272800.000	18			
	GRE	5320400.000	18			
Corrected Total	SAT	67111.111	17			
	GRE	71600.000	17			

a. R Squared = .046 (Adjusted R Squared = -.081)
 b. R Squared = .073 (Adjusted R Squared = -.051)

IBM SPSS Statistics Processor is ready | Unicode.ON | H: 164, W: 812 pt

Drawing Conclusions

We interpret the results of the univariate tests only if the group *Wilks' Lambda* is significant. Our results are not significant, but we will first consider how to interpret results that are significant.

Phrasing Results That Are Significant

If we had received the output on the next page (which can be obtained by changing the group 2 values for SAT to 580, 620, 590, 630, 620, and 680), we would have had a

significant MANOVA. Note that we would also select *Post Hoc* and had SPSS compute Tukey's HSD for the variable GROUP.

IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- General Linear Model
 - Title
 - Notes
 - Between-Subjects Factors
 - Multivariate Tests
 - Tests of Between-Subjects Effects
 - Post Hoc Tests
 - Title
 - GROUP
 - Title
 - Multiple Comparisons
 - Homogeneous Subsets
 - Title
 - SAT
 - GRE

General Linear Model

Between-Subjects Factors

	Value	Label	N
GROUP	0 0	No Training	6
	1 00	Short Term	6
	2 00	Long Term	6

Multivariate Tests^a

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.990	663.040 ^b	2.000	14.000	.000
	Wilks' Lambda	.010	663.040 ^b	2.000	14.000	.000
	Hotelling's Trace	94.720	663.040 ^b	2.000	14.000	.000
	Roy's Largest Root	94.720	663.040 ^b	2.000	14.000	.000
GROUP	Pillai's Trace	.604	3.245	4.000	30.000	.025
	Wilks' Lambda	.398	4.099 ^b	4.000	28.000	.010
	Hotelling's Trace	1.510	4.906	4.000	26.000	.004
	Roy's Largest Root	1.507	11.293 ^c	2.000	15.000	.001

a. Design: Intercept * GROUP
 b. Exact statistic
 c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	SAT	33411.111 ^a	2	16705.556	4.213	.035
	GRE	5200.000 ^b	2	2600.000	.587	.568
Intercept	SAT	5633605.556	1	5633605.556	1420.635	.000
	GRE	5248800.000	1	5248800.000	1185.723	.000
GROUP	SAT	33411.111	2	16705.556	4.213	.035
	GRE	5200.000	2	2600.000	.587	.568
Error	SAT	59483.333	15	3965.556		
	GRE	66400.000	15	4426.667		
Total	SAT	5726500.000	18			
	GRE	5320400.000	18			
Corrected Total	SAT	92894.444	17			
	GRE	71600.000	17			

a. R Squared = .360 (Adjusted R Squared = .274)
 b. R Squared = .073 (Adjusted R Squared = -.051)

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 124, W: 741 pt.

We could state the following:

A one-way MANOVA was calculated examining the effect of training (none, short-term, or long-term) on SAT and GRE scores. A significant effect was found ($\text{Lambda}(4,28) = .398, p = .010$). Follow-up univariate ANOVAs indicated that SAT scores were significantly improved by training ($F(2,15) = 4.213, p = .035$). GRE scores were not significantly improved by training ($F(2,15) = .587, p > .05$).

Phrasing Results That Are Not Significant

The actual example presented (based upon the *SAT.sav* data file) was not significant. Therefore, we could state the following in the results section:

A one-way MANOVA was calculated examining the effect of training (none, short-term, or long-term) on *SAT* and *GRE* scores. No significant effect was found ($\Lambda(4,28) = .828, p > .05$). Neither *SAT* nor *GRE* scores were significantly influenced by training.

significant MANOVA. Note that we would also select *Post Hoc* and had SPSS compute Tukey's HSD for the variable GROUP.

SPSS Statistics Viewer - *Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- General Linear Model
 - Title
 - Notes
 - Between-Subjects Factors
 - Multivariate Tests
 - Tests of Between-Subjects Effects
 - Post Hoc Tests
 - Title
 - GROUP
 - Title
 - Multiple Comparisons
 - Homogeneous Subsets
 - Title
 - SAT
 - GRE

General Linear Model

Between-Subjects Factors

	value	Label	N
GROUP	0 0	No Training	6
	1 00	Short Term	6
	2 00	Long Term	6

Multivariate Tests^a

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.990	663.040 ^b	2.000	14.000	.000
	Wilks' Lambda	.010	663.040 ^b	2.000	14.000	.000
	Hotelling's Trace	94.720	663.040 ^b	2.000	14.000	.000
	Roy's Largest Root	94.720	663.040 ^b	2.000	14.000	.000
GROUP	Pillai's Trace	.604	3.245	4.000	30.000	.025
	Wilks' Lambda	.398	4.099 ^b	4.000	28.000	.010
	Hotelling's Trace	1.510	4.906	4.000	26.000	.004
	Roy's Largest Root	1.507	11.299 ^c	2.000	15.000	.001

a. Design: Intercept + GROUP
 b. Exact statistic
 c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	SAT	33411.111 ^a	2	16705.556	4.213	.035
	GRE	5200.000 ^b	2	2600.000	.587	.568
Intercept	SAT	5633605.556	1	5633605.556	1420.635	.000
	GRE	5246800.000	1	5246800.000	1185.723	.000
GROUP	SAT	33411.111	2	16705.556	4.213	.035
	GRE	5200.000	2	2600.000	.587	.568
Error	SAT	59483.333	15	3965.556		
	GRE	65400.000	15	4426.667		
Total	SAT	5726500.000	18			
	GRE	5320400.000	18			
Corrected Total	SAT	92894.444	17			
	GRE	71600.000	17			

a. R Squared = .360 (Adjusted R Squared = .274)
 b. R Squared = .073 (Adjusted R Squared = -.051)

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 124, W: 741 pt

We could state the following:

A one-way MANOVA was calculated examining the effect of training (none, short-term, or long-term) on SAT and GRE scores. A significant effect was found ($\text{Lambda}(4,28) = .398, p = .010$). Follow-up univariate ANOVAs indicated that SAT scores were significantly improved by training ($F(2,15) = 4.213, p = .035$). GRE scores were not significantly improved by training ($F(2,15) = .587, p > .05$).

Phrasing Results That Are Not Significant

The actual example presented (based upon the SAT.sav data file) was not significant. Therefore, we could state the following in the results section:

A one-way MANOVA was calculated examining the effect of training (none, short-term, or long-term) on SAT and GRE scores. No significant effect was found ($\Lambda(4,28) = .828, p > .05$). Neither SAT nor GRE scores were significantly influenced by training.

Chapter 8

Nonparametric Inferential Statistics

Nonparametric tests are used when the corresponding parametric procedure is inappropriate. Normally, this is because the **dependent variable** is not **interval- or ratio-scaled**. It can also be because the **dependent variable** is not normally distributed. If the data of interest are frequency counts, nonparametric statistics may also be appropriate.

SPSS has a powerful *Nonparametric Tests* command that includes enhanced reports, which help users choose the appropriate test and interpret the result correctly.

Section 8.1 Chi-Square Goodness of Fit Description

The chi-square goodness of fit test determines whether or not sample proportions match the theoretical values. For instance, it could be used to determine if a die is loaded or fair. It could also be used to compare the proportion of children born with birth defects to the population value (e.g., to determine if a certain neighborhood has a statistically higher-than-normal rate of birth defects).

Assumptions

We need to make very few assumptions. There are no assumptions about the shape of the distribution. The expected frequencies for each category should be at least 1, and no more than 20 percent of the categories should have expected frequencies of less than 5.

SPSS Data Format

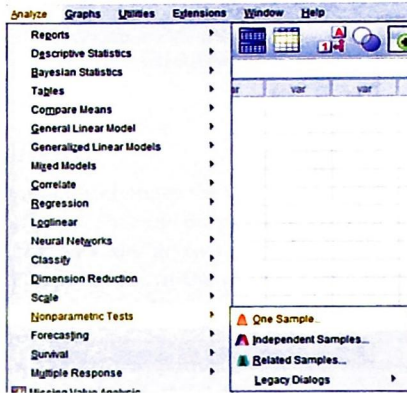
SPSS requires only a single variable. It can be measured on any scale, although SPSS requires it to be defined as nominal.

Running the Command

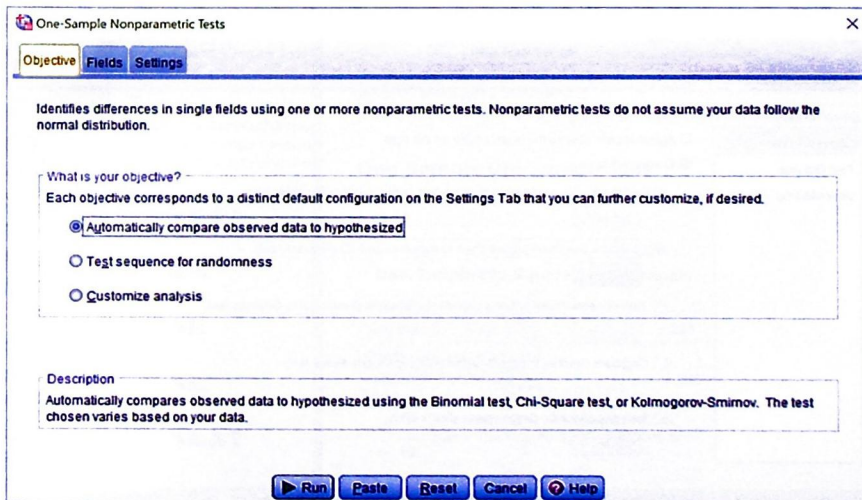
We will create the following dataset and call it COINS.sav. The following data represent the flipping of each of two coins 20 times (H is coded as heads, T as tails).

Coin 1: H T H H T H H T H H H T T T H T H T T H
Coin 2: T T H H T H T H T T H H T H H T H T H H

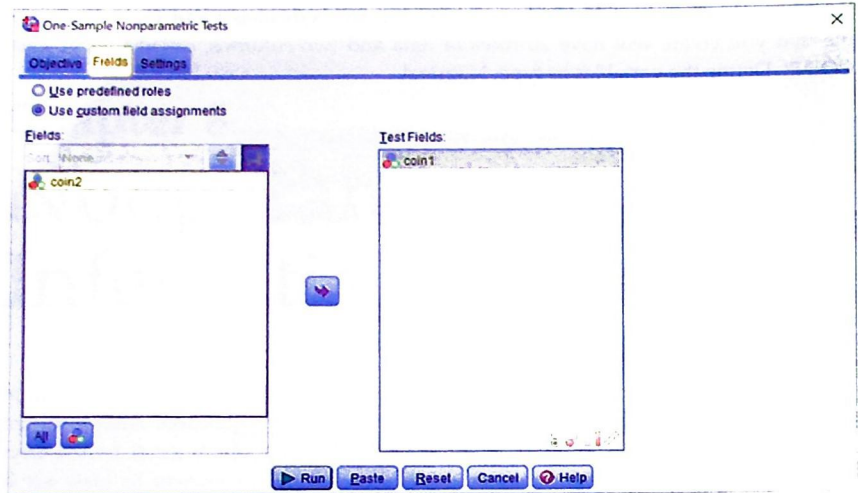
Name the two variables COIN1 and COIN2, and code H as 1 and T as 2. The data file that you create will have 20 rows of data and two columns, called COIN1 and COIN2. Define the variables as type: Nominal.



To run the *Chi-Square* command, click *Analyze*, then *Nonparametric Tests*, then *One Sample*. This will bring up the dialog box for the *One-Sample Nonparametric Tests* command. You will notice that this new procedure has a dialog box that is quite different from the interfaces for other SPSS commands. It was completely rewritten using SPSS's new modeling procedures starting with Version 18.

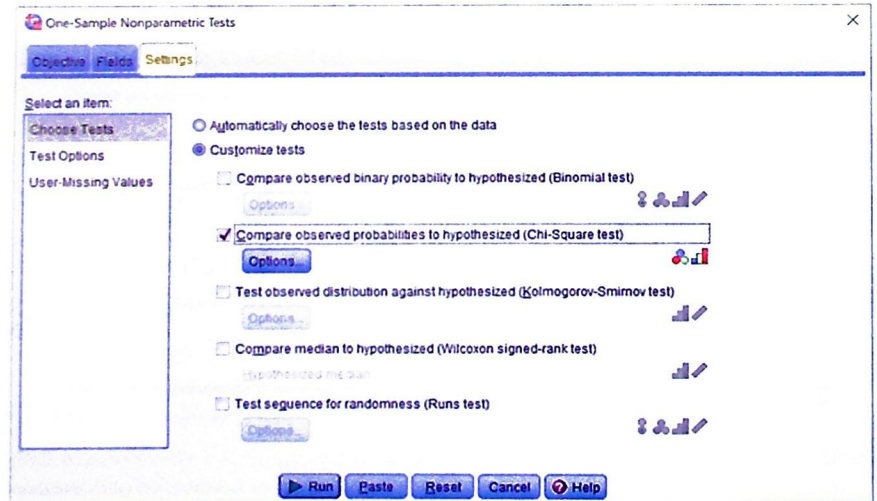


Our objective for a chi-square goodness of fit test is to determine if the distribution of the data is equal to the hypothesized distribution. Therefore, just leave the *Objective* tab the same and click on the *Fields* tab at the top of the window.

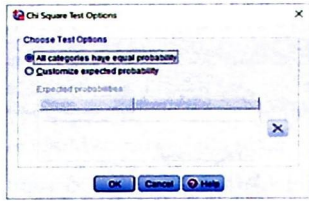


You will need to click *Use custom field assignments* and then move the variable COIN1 to the *Test Fields* area on the right.

This new procedure is actually quite smart and will examine your data and choose the most appropriate test for you. In order to demonstrate the chi-square test of independence, however, we will force it to run only that test by selecting the *Settings* tab across the top, then clicking *Customize tests* under *Choose Tests*, and then checking the *Compare observed probabilities to hypothesized (Chi-Square test)* option.



A fair coin has an equal chance of coming up heads or tails. Therefore, there is nothing further we need to do. If, however, different values had different expected probabilities, we would click *Options*, where we would have an opportunity to *Customize expected probability*. Close the Chi-Square Test Options window by clicking *Cancel*, and then click *Run*.



Reading the Output

This new procedure completely changes the way output is presented when compared with other procedures in SPSS. The new output states the **null hypothesis** in standard English, tells you what test was run, gives a **significance level**, and tells you whether or not to reject the **null hypothesis**. In the example shown here, we are clearly told that the one-sample chi-square test (chi-square goodness of fit test) tested whether the values of COIN1 had equal probabilities (50% chance of heads and 50% chance of tails). We were told to “Retain the **null hypothesis**” (which most standard statistics texts would call “fail to reject the **null hypothesis**”).

Nonparametric Tests

Hypothesis Test Summary

	Null Hypothesis	Test	Sig	Decision
1	The categories of coin1 occur with equal probabilities.	One-Sample Chi-Square Test	.655	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .050.

One-Sample Chi-Square Test

coin1

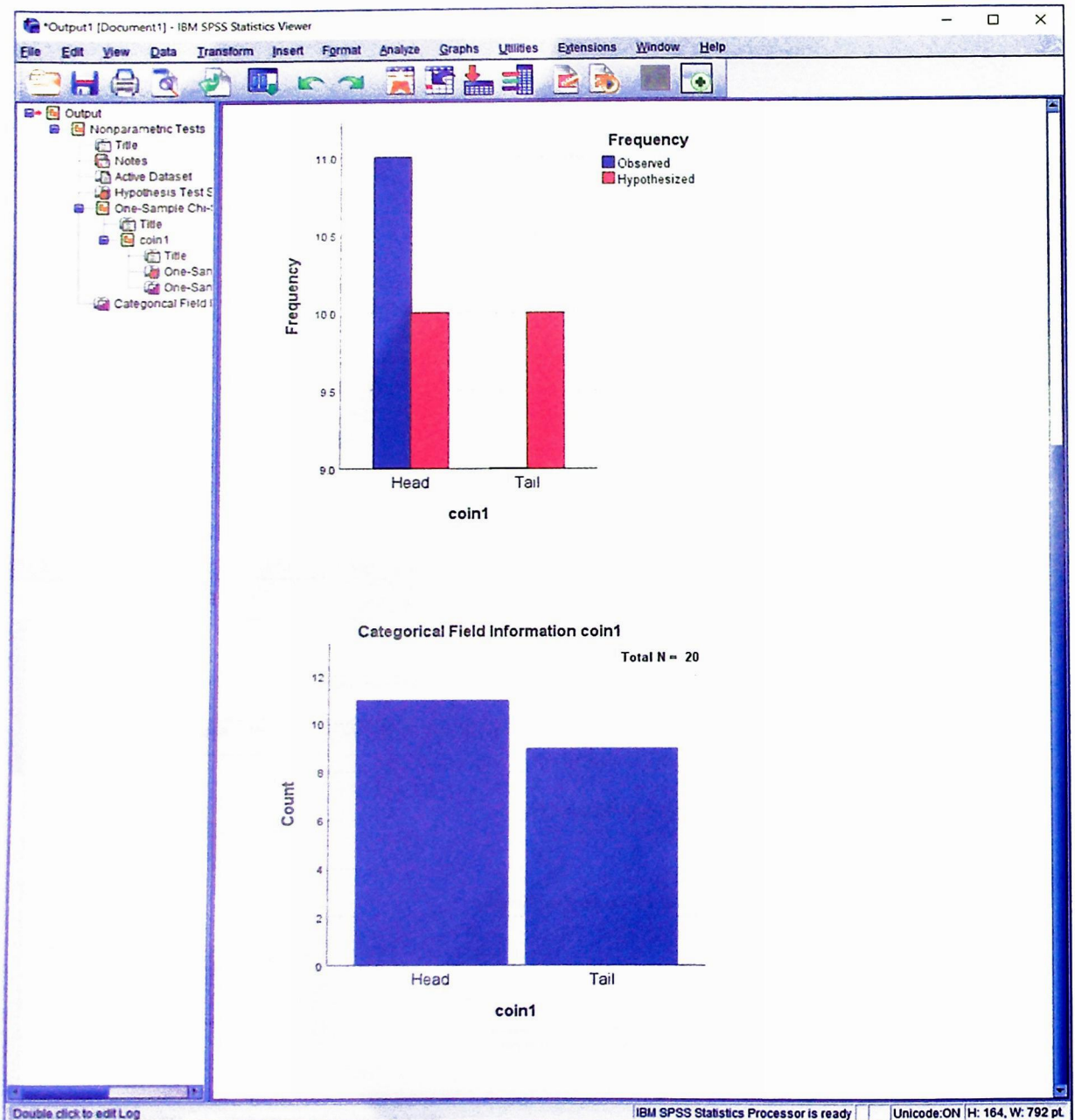
One-Sample Chi-Square Test Summary

Total N	20
Test Statistic	.200 ^a
Degree Of Freedom	1
Asymptotic Sig (2-sided test)	.655

a. There are 0 cells (0%) with expected values less than 5. The minimum expected value is 10.

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 118, W: 707 pt.

Under the text output is a graphical representation of the analysis.



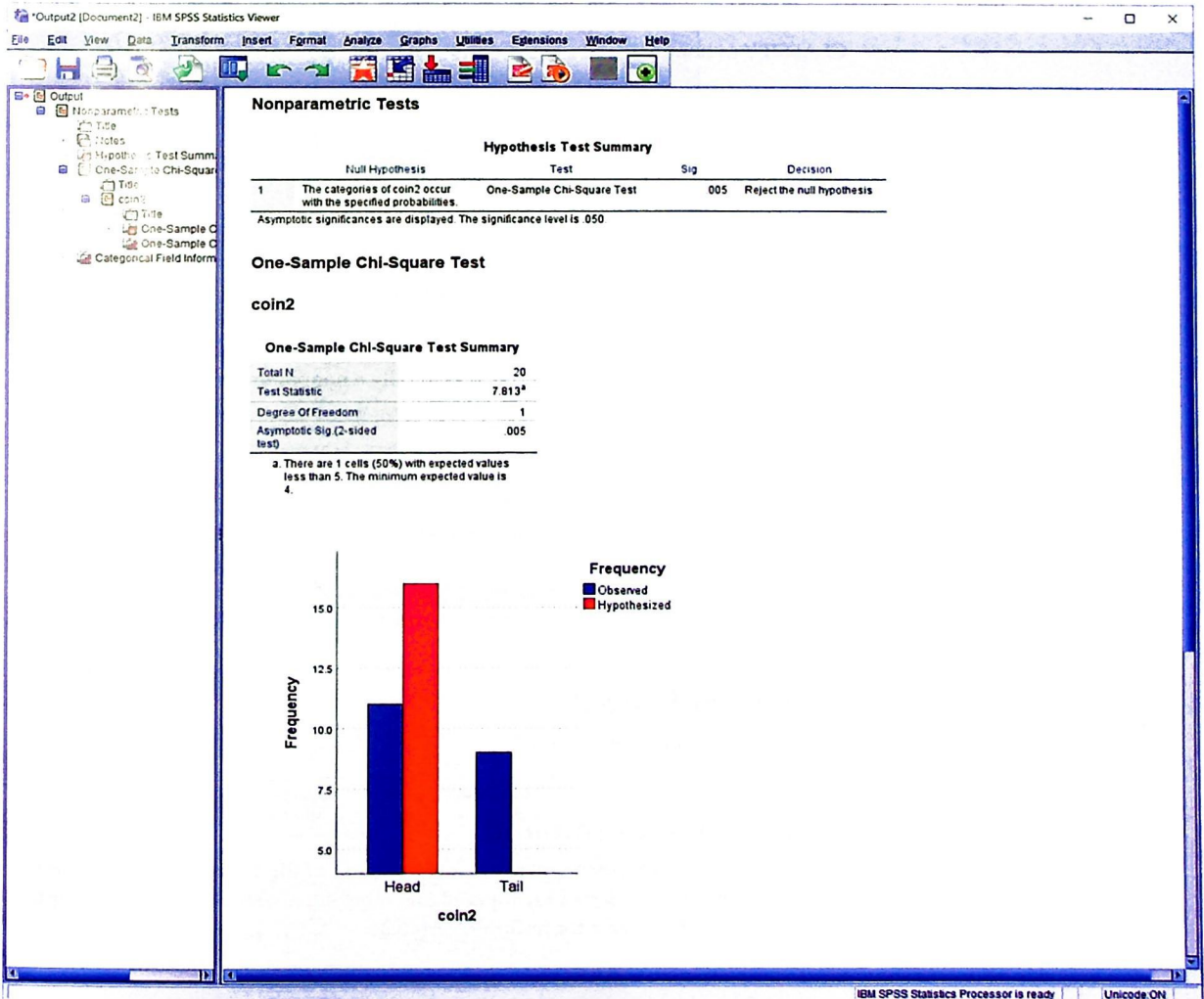
Drawing Conclusions

A significant chi-square test indicates that the data vary from the expected values. A test that is not significant indicates that the data are consistent with the expected values.

Phrasing Results That Are Significant

In describing the results, you should state the value of chi-square (whose symbol is χ^2), the degrees of freedom, the **significance level**, and a description of the results. For instance, with a significant chi-square (this output compares COIN2 to hypothesized proportions of 80 and 20), we could state the following:

A chi-square goodness of fit test was calculated comparing the frequency of occurrence of each Heads and Tails on a coin. It was hypothesized that Heads would occur 80% of the time. Significant deviation from the hypothesized values was found ($\chi^2 (1) = 7.813, p < .05$). The coin does not appear to be biased to come up Head 80% of the time.



Phrasing Results That Are Not Significant

If the analysis produces no significant difference, as in the original example, we could state the following:

A chi-square goodness of fit test was calculated comparing the frequency of occurrence of heads and tails on a coin. It was hypothesized that each value would occur an equal number of times. No significant deviation from the hypothesized values was found ($\chi^2(1) = .20, p > .05$). The coin appears to be fair.

Practice Exercise

Use Practice Dataset 2 in Appendix B. In the population from which the sample was drawn, 20 percent of employees are clerical, 50 percent are technical, and 30 percent are professional. Determine whether or not the sample drawn conforms to these values. Hint: You will need to *customize expected probabilities* and enter the category values (1, 2, 3) and relative percentages (20, 50, 30). Also, be sure you have entered the variable CLASSIFY as nominal.

Section 8.2 Chi-Square Test of Independence

Description

The chi-square test of independence tests whether or not two variables are independent of each other. For instance, flips of a coin should be **independent events**, so knowing the outcome of one coin toss should not tell us anything about the second coin toss. The chi-square test of independence is essentially a nonparametric version of the **interaction** term in ANOVA.

Assumptions

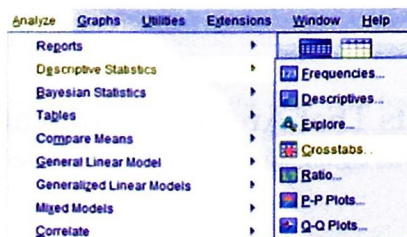
Very few assumptions are needed. For instance, we make no assumptions about the shape of the distribution. The expected frequencies for each category should be at least 1, and no more than 20 percent of the categories should have expected frequencies of less than 5. (Note: To save space, these examples violate that assumption.)

SPSS Data Format

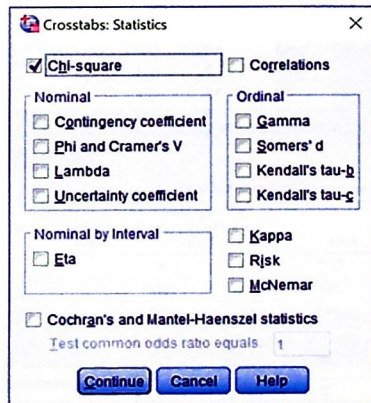
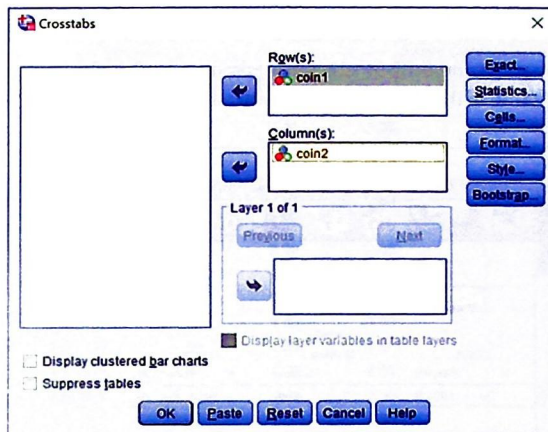
At least two variables are required.

Running the Command

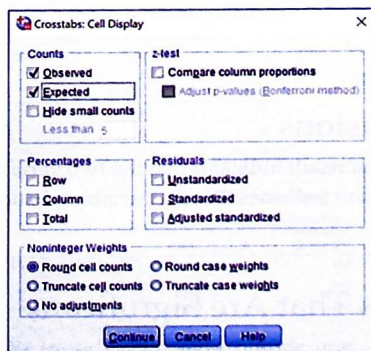
The chi-square test of independence is a component of the *Crosstabs* command rather than the *Nonparametric Statistics* command. For more details, see Section 3.2 in Chapter 3 on frequency distributions for multiple variables.



This example uses the COINS.sav file. COIN1 is placed in the *Row(s)* blank, and COIN2 is placed in the *Column(s)* blank.



Click *Statistics*, then check the *Chi-square* box. Click *Continue*. You may also want to click *Cells* to select expected frequencies in addition to observed frequencies.



Note that you can also use the *Cells* option to display the percentages of each variable for each value. This is especially useful when your groups are different sizes, but it is unnecessary in this example.

Click *OK* to run the analysis.

Reading the Output

The output consists of two parts. The first part gives you the counts. In this example, the actual and expected frequencies are shown because they were selected with the *Cells* option.

The second part of the output gives the results of the chi-square test. The most commonly used value is the Pearson chi-square, shown in the first row (value of .737).

The screenshot shows the IBM SPSS Statistics Viewer window with the following output:

Crosstabs

Case Processing Summary

	Valid		Cases Missing		Total	
	N	Percent	N	Percent	N	Percent
coin1 * coin2	20	100.0%	0	0.0%	20	100.0%

coin1 * coin2 Crosstabulation

		coin2		Total
		Head	Tail	
coin1	Head	Count 7	4	11
		Expected Count 6.1	5.0	11.0
Tail	Count 4	5	9	
		Expected Count 5.0	4.1	9.0
Total	Count 11	9	20	
		Expected Count 11.0	9.0	20.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.737 ^a	1	.391		
Continuity Correction ^b	.165	1	.684		
Likelihood Ratio	.740	1	.390		
Fisher's Exact Test				.653	.342
Linear-by-Linear Association	.700	1	.403		
N of Valid Cases	20				

^a 3 cells (75.0%) have expected count less than 5. The minimum expected count is 4.05.
^b Computed only for a 2x2 table.

Drawing Conclusions

A significant chi-square test result indicates that the two variables are not independent. A value that is not significant indicates that the variables do not vary significantly from independence.

Phrasing Results That Are Significant

In describing the results, you should give the value of chi-square, the degrees of freedom, the **significance** level, and a description of the results. For instance, with a significant chi-square (for a dataset different from the one discussed above), we could state the following: These results can be obtained with the following data, testing COIN1 and COIN3.

*coins.sav [DataSet5] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extension Window Help

Visible: 3 of 3 Variables

	coin1	coin2	coin3	var	va
1	1.00	2.00	1.00		
2	2.00	2.00	2.00		
3	1.00	1.00	1.00		
4	1.00	1.00	1.00		
5	2.00	2.00	2.00		
6	1.00	1.00	1.00		
7	1.00	2.00	1.00		
8	2.00	1.00	2.00		
9	1.00	2.00	1.00		
10	1.00	2.00	1.00		
11	1.00	1.00	1.00		
12	2.00	1.00	2.00		
13	2.00	2.00	2.00		
14	2.00	1.00	2.00		
15	1.00	1.00	1.00		
16	2.00	2.00	2.00		
17	1.00	1.00	1.00		
18	2.00	2.00	2.00		
19	2.00	1.00	1.00		
20	1.00	1.00	2.00		
21					

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

*Output2 [Document2] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Crosstabs
 - Title
 - Notes
 - Case Processing Summary
 - coin1 * coin3 Crosstabulation
 - Chi-Square Tests

Crosstabs

Case Processing Summary

	Valid		Cases Missing		Total	
	N	Percent	N	Percent	N	Percent
coin1 * coin3	20	100.0%	0	0.0%	20	100.0%

coin1 * coin3 Crosstabulation

Count

coin1	Head	coin3		Total
		1.00	2.00	
Head	10	1	11	
Tail	1	8	9	
Total	11	9	20	

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square ^a	12.735 ^a	1	.000		
Continuity Correction ^b	9.715	1	.002		
Likelihood Ratio	14.545	1	.000		
Fisher's Exact Test				.001	.001
Linear-by-Linear Association	12.099	1	.001		
N of Valid Cases	20				

a. 3 cells (75.0%) have expected count less than 5. The minimum expected count is 4.05.
b. Computed only for a 2x2 table.

Log is visible

IBM SPSS Statistics Processor is ready Unicode:ON H: 124, W: 1036 pt

A chi-square test of independence was calculated comparing whether flips of a coin were independent. A significant interaction was found ($\chi^2(1) = 12.735, p < .05$). The flips of a coin were dependent on each other.

Phrasing Results That Are Not Significant

A chi-square test that is not significant indicates that there is no significant dependence of one variable on the other. The coin original (COIN1 and COIN2) example was not significant. Therefore, we could state the following:

A chi-square test of independence was calculated comparing the results of flipping two coins. No significant relationship was found ($\chi^2(1) = .737, p > .05$). Flips of a coin appear to be independent events.

Practice Exercise

A researcher wants to know if individuals are more likely to help in an emergency when they are indoors or when they are outdoors. Of 28 participants who were outdoors, 19 helped and 9 did not. Of 23 participants who were indoors, 8 helped and 15 did not. Enter these data, and find out if helping behavior is affected by the environment. The key to this problem is in the data entry. Hint: How many participants were there, and how many pieces of information do we know about each? Having SPSS give you cell percentages will help you with the interpretation of this problem.

Section 8.3 Mann-Whitney *U* Test

Description

The Mann-Whitney *U* test is the nonparametric equivalent of the independent *t* test. It tests whether or not two independent samples are from the same distribution. The Mann-Whitney *U* test is weaker than the independent *t* test, and the *t* test should be used if you can meet its assumptions.

Assumptions

The Mann-Whitney *U* test uses the rankings of the data. Therefore, the data for the two samples must at least be **ordinal**. There are no assumptions about the shape of the distribution.

SPSS Data Format

This command requires a single variable representing the **dependent variable** and a second variable indicating group membership. SPSS requires the **dependent variable** to be a scale-type variable even though the variable itself only needs to be **ordinal**.

Running the Command

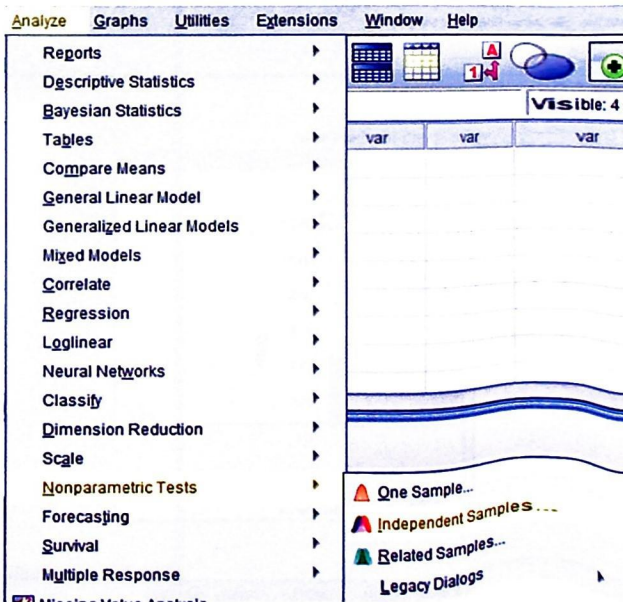
This example will use a new data file. It represents eight participants in a series of races. There were long races, medium races, and short races. Participants were either experienced (2) or had medium experience (1).

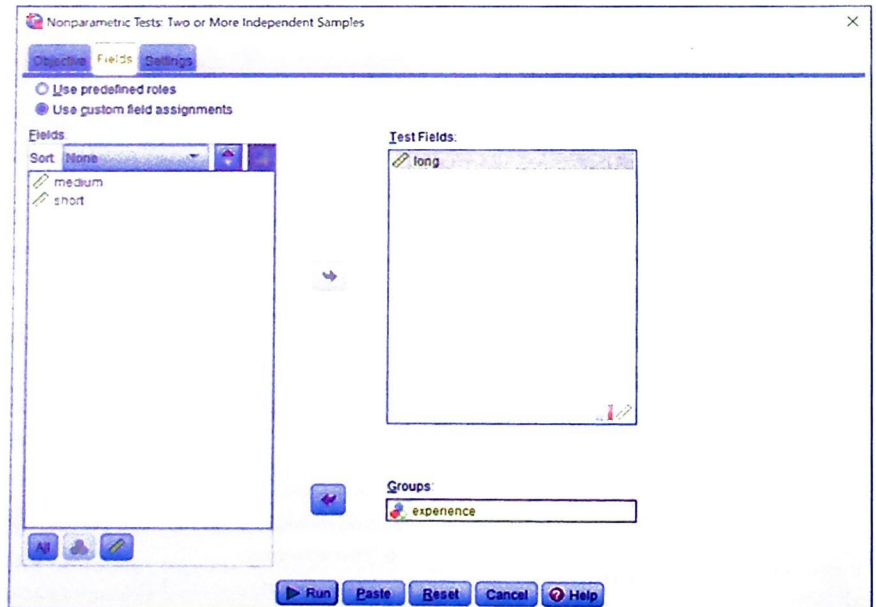
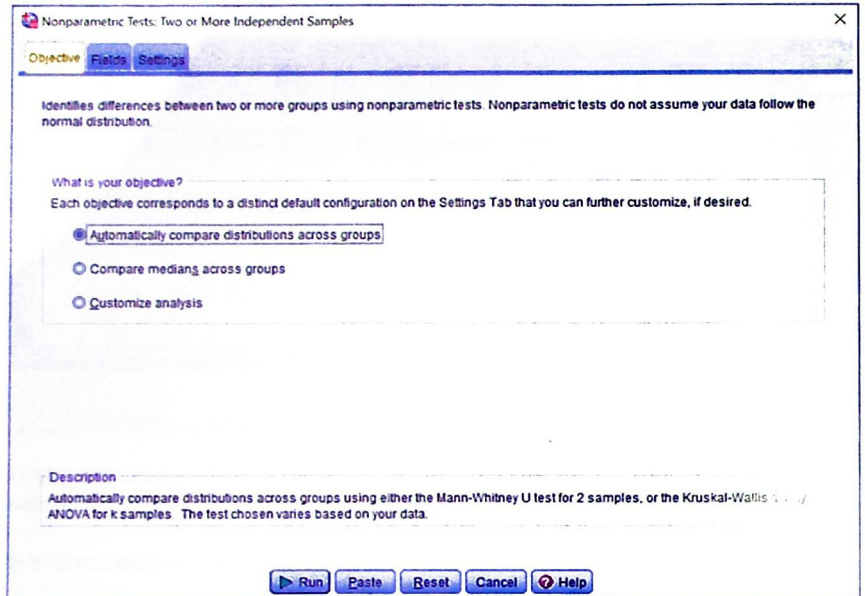
	long	medium	short	experience
1	1.00	4.00	6.00	2.00
2	2.00	3.00	4.00	2.00
3	3.00	2.00	7.00	2.00
4	4.00	5.00	3.00	2.00
5	5.00	1.00	10.00	1.00
6	6.00	8.00	5.00	1.00
7	7.00	7.00	12.00	1.00
8	8.00	6.00	1.00	1.00
9				

Enter the data from the figure shown above in a new file, and **save** the data file as RACE.sav. The values for LONG, MEDIUM, and SHORT represent the results of the race, with 1 being first place and 8 being last.

Make sure that LONG, MEDIUM, and SHORT are scale-type variables and that EXPERIENCE is a nominal-type variable.

To run the command, click *Analyze*, then *Nonparametric Tests*, then *Independent Samples*. This will bring up the main dialog box.





Leave the *Objective* to *Automatically compare distributions across groups*. Then click on the *Fields* tab. Next, enter EXPERIENCE in the *Groups* area. Click on *Run* to perform the analysis.

Reading the Output

Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Nonparametric Tests
 - Title
 - Notes
 - Hypothesis Test Summary
 - Independent-Samples Mann-W
 - Title
 - long across experience
 - Independent-Samples
 - Independent-Samples
 - Continuous Field Information lo
 - Categorical Field Information ex

Nonparametric Tests

Hypothesis Test Summary				
	Null Hypothesis	Test	Sig.	Decision
1	The distribution of long is the same across categories of experience.	Independent-Samples Mann-Whitney U Test	.029 ^a	Reject the null hypothesis

Asymptotic significances are displayed. The significance level is .050.

a. Exact significance is displayed for this test.

Independent-Samples Mann-Whitney U Test

long across experience

Independent-Samples Mann-Whitney U Test Summary

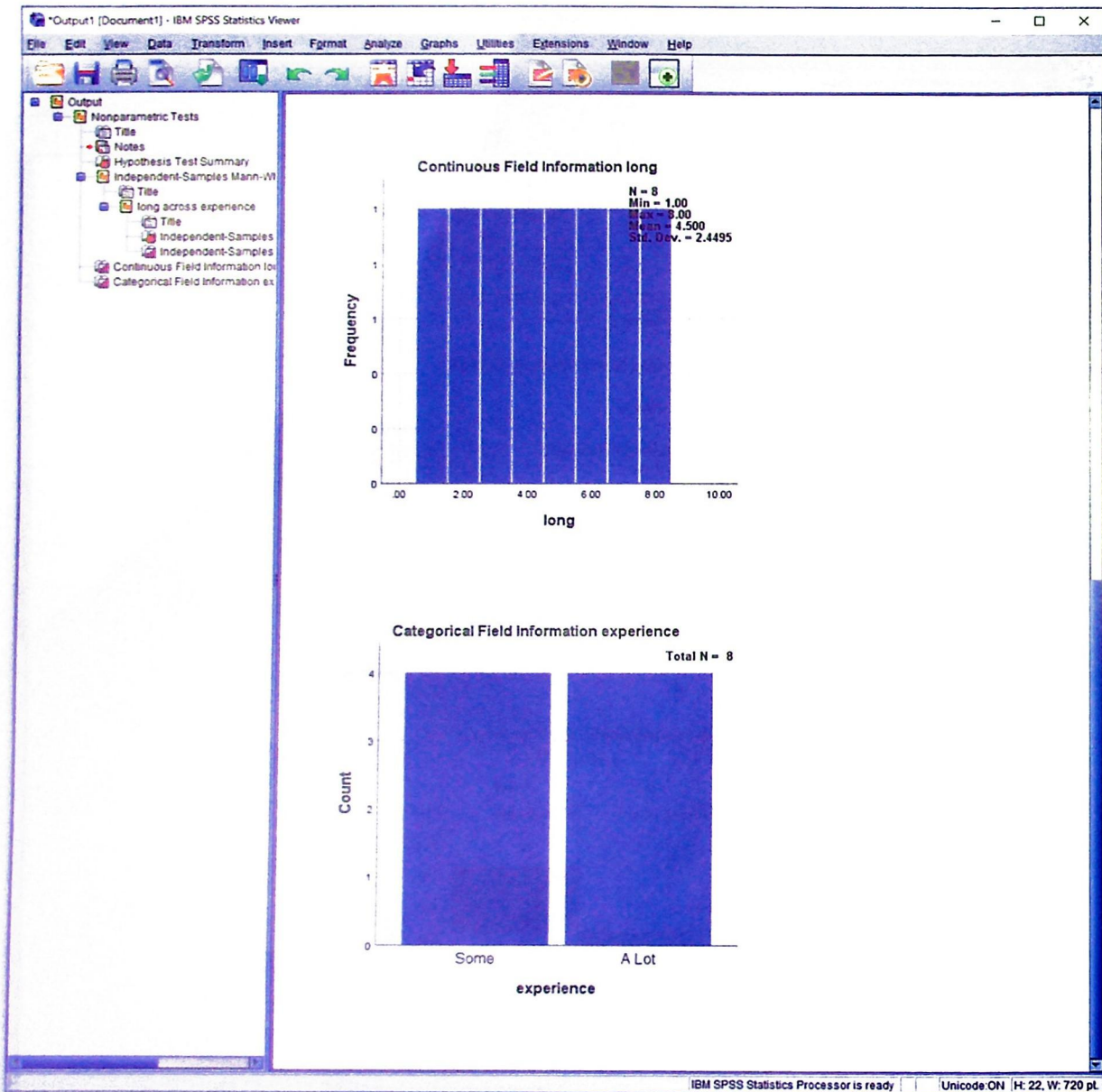
Total N	8
Mann-Whitney U	.000
Wilcoxon W	10.000
Test Statistic	.000
Standard Error	3.464
Standardized Test Statistic	-2.309
Asymptotic Sig. (2-sided test)	.021
Exact Sig. (2-sided test)	.029

Independent-Samples Mann-Whitney U Test

experience

Experience Category	N	Mean Rank
A Lot	4	2.50
Some	4	6.50

IBM SPSS Statistics Processor is ready | Unicode.ON | H: 22, W: 7



Here you will get a plain-English result. In this case, we reject the **null hypothesis** that the distribution was the same for both levels of experience.

The output consists of several sections. One section gives **descriptive statistics** for the two samples. Because the data are required only to be at least **ordinal**, summaries relating to their ranks are used. Those participants who had medium experience averaged 6.5 as their place in the race. The experienced participants averaged 2.5 as their place in the race.

Another section of the output is the result of the Mann-Whitney U test itself. The value obtained was 0.0, with a **significance level** of .029.

Drawing Conclusions

A significant Mann-Whitney U result indicates that the two samples are different in terms of their average ranks.

Phrasing Results That Are Significant

Our preceding example is significant, so we could state the following:

A Mann-Whitney U test was calculated examining the place that runners with varying levels of experience took in a long-distance race. Runners with medium levels of experience did significantly worse (M place = 6.50) than experienced runners (M place = 2.50; $U = 0.00$, $p < .05$).

Phrasing Results That Are Not Significant

If we ran the test on short-distance races instead of long we would get the following output:

The screenshot displays the SPSS Statistics Viewer interface. The main window shows the following output:

Nonparametric Tests

Hypothesis Test Summary				
	Null Hypothesis	Test	Sig.	Decision
1	The distribution of short is the same across categories of experience.	Independent-Samples Mann-Whitney U Test	.686 ^a	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .050.
a. Exact significance is displayed for this test.

Independent-Samples Mann-Whitney U Test

short across experience

Independent-Samples Mann-Whitney U Test Summary	
Total N	8
Mann-Whitney U	6.000
Wilcoxon W	16.000
Test Statistic	6.000
Standard Error	3.464
Standardized Test Statistic	-.577
Asymptotic Sig. (2-sided test)	.564
Exact Sig. (2-sided test)	.686

Independent-Samples Mann-Whitney U Test

experience

The notched box plot shows the distribution of 'short' for two experience levels. The 'A Lot' group (N=4, Mean Rank=4.00) has a notched box from approximately 2.5 to 7.5. The 'Some' group (N=4, Mean Rank=5.00) has a notched box from approximately 2.5 to 10.0. The notches do not overlap, suggesting a difference in the distributions.

A Mann-Whitney U test was used to examine the difference in the race performance of runners with medium experience and runners with experience in a short-distance race. No significant difference in the results of the race was found ($U = 6.00, p > .05$). Runners with medium experience averaged a place of 5. Experienced runners averaged 4.

Practice Exercise

Using Practice Dataset 1 in Appendix B, determine if younger participants (< 26) have significantly lower mathematics scores than older participants. (Note: You will need to create a new ordinal variable representing each age group. See Section 2.2 if you need a refresher on how to do that.)

Section 8.4 Wilcoxon Test

Description

The Wilcoxon test is the nonparametric equivalent of the paired-samples (dependent) t test. It tests whether or not two related samples are from the same distribution. The Wilcoxon test is weaker than the independent t test, so the t test should be used if you can meet its assumptions.

Assumptions

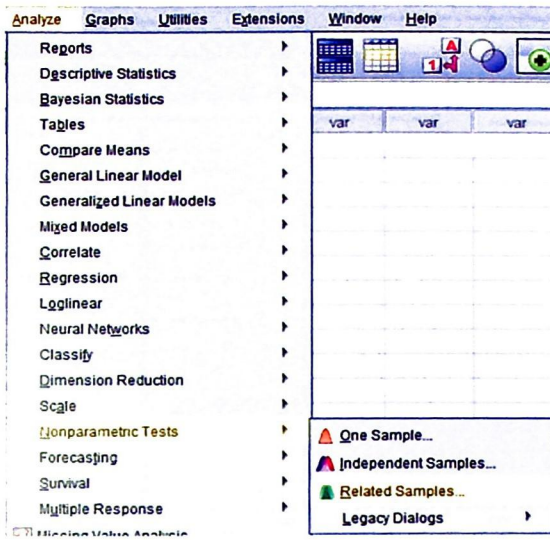
The Wilcoxon test is based on the difference in rankings. The data for the two samples must at least be **ordinal**. There are no assumptions about the shape of the distribution.

SPSS Data Format

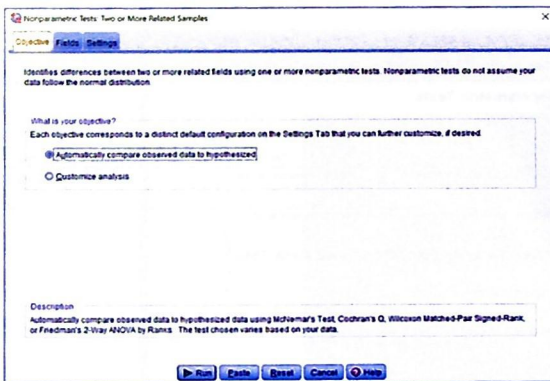
The test requires two variables. One variable represents the **dependent variable** at the first level of the **independent variable**. The other variable represents the **dependent variable** at the second level of the **independent variable**.

Running the Command

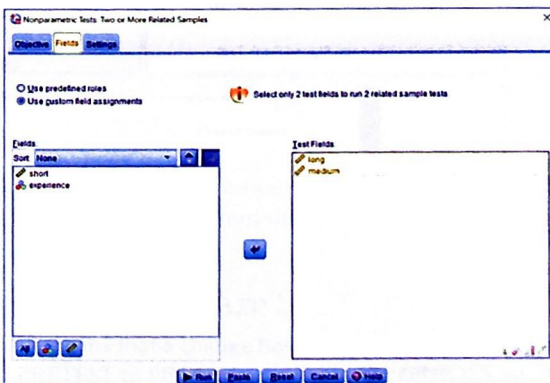
Locate the command by clicking *Analyze*, then *Nonparametric Tests*, then *Related Samples*. This example uses the RACE.sav dataset.



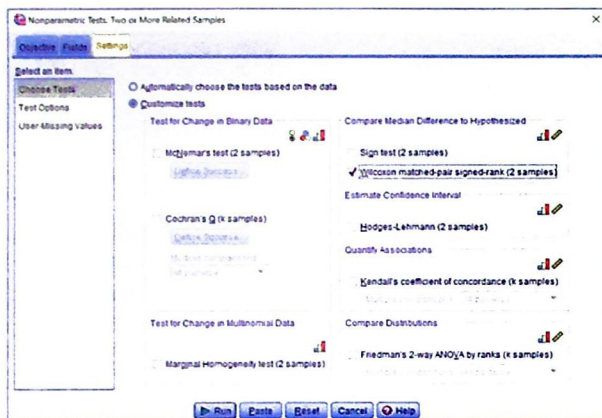
First, you will be presented with the Nonparametric Tests dialog box.



Select the *Fields* tab. Move the variables LONG and MEDIUM over to the *Test Fields* area as shown below.

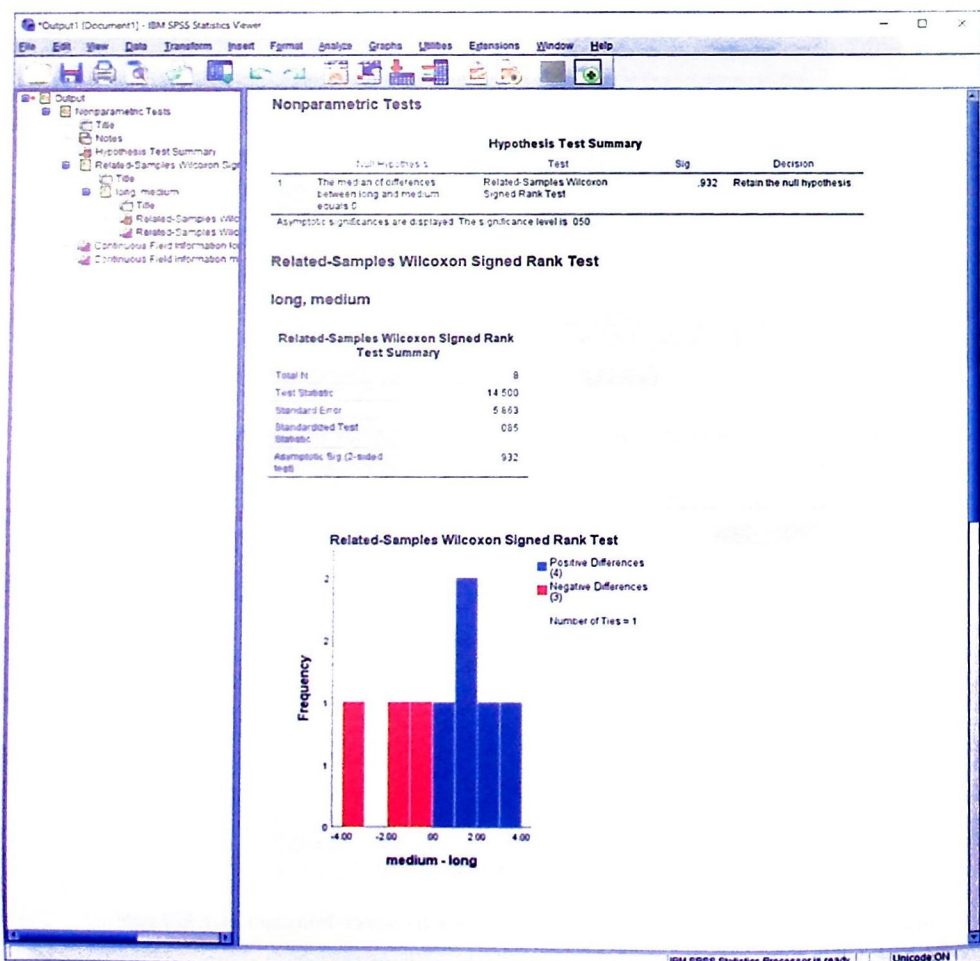


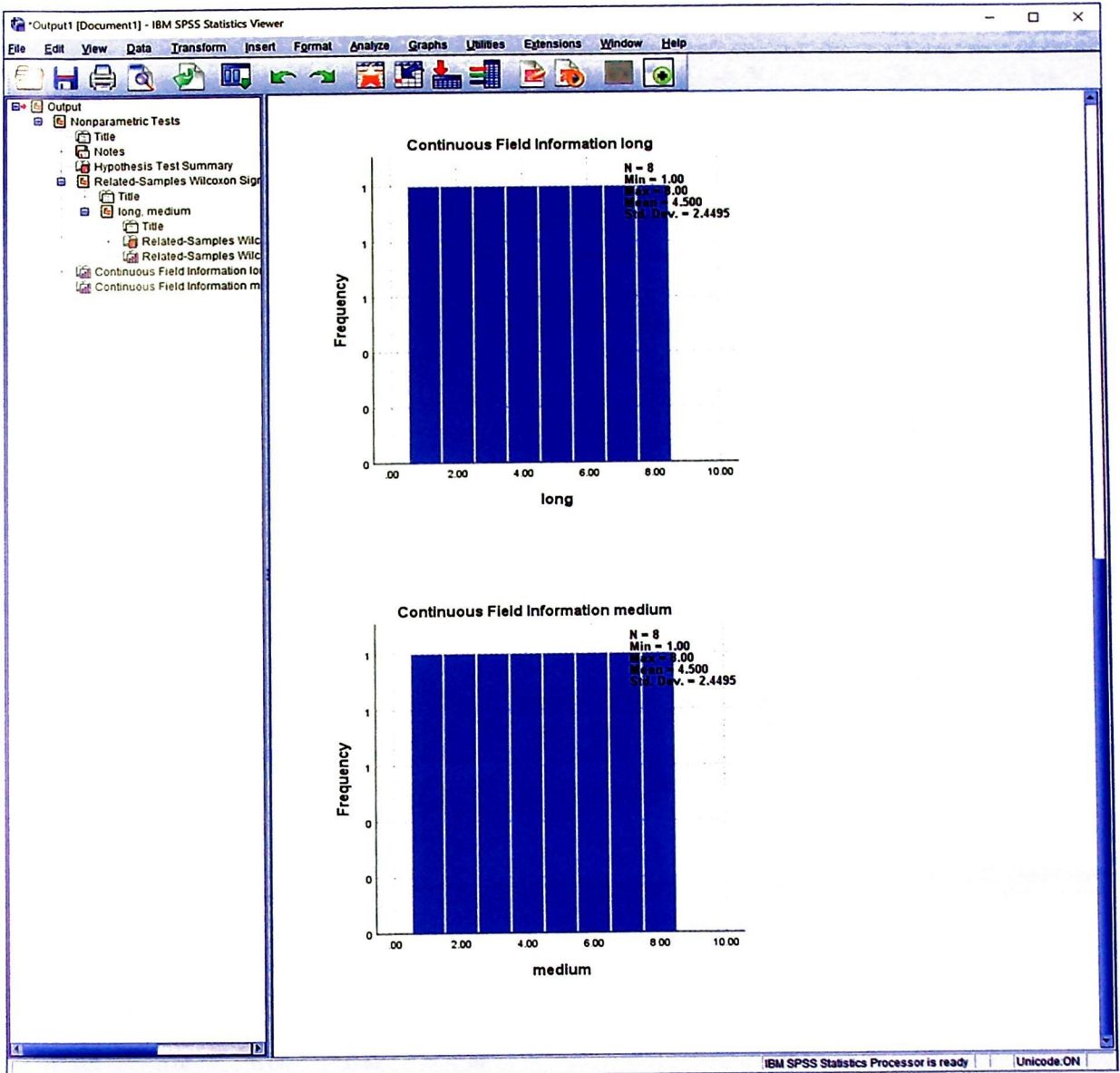
Finally, select the *Settings* tab and *Customize tests* to select *Wilcoxon matched-pair signed-rank*. Click *Run*.



Reading the Output

As part of the new nonparametric procedure, the output will be presented in plain English with graphs.

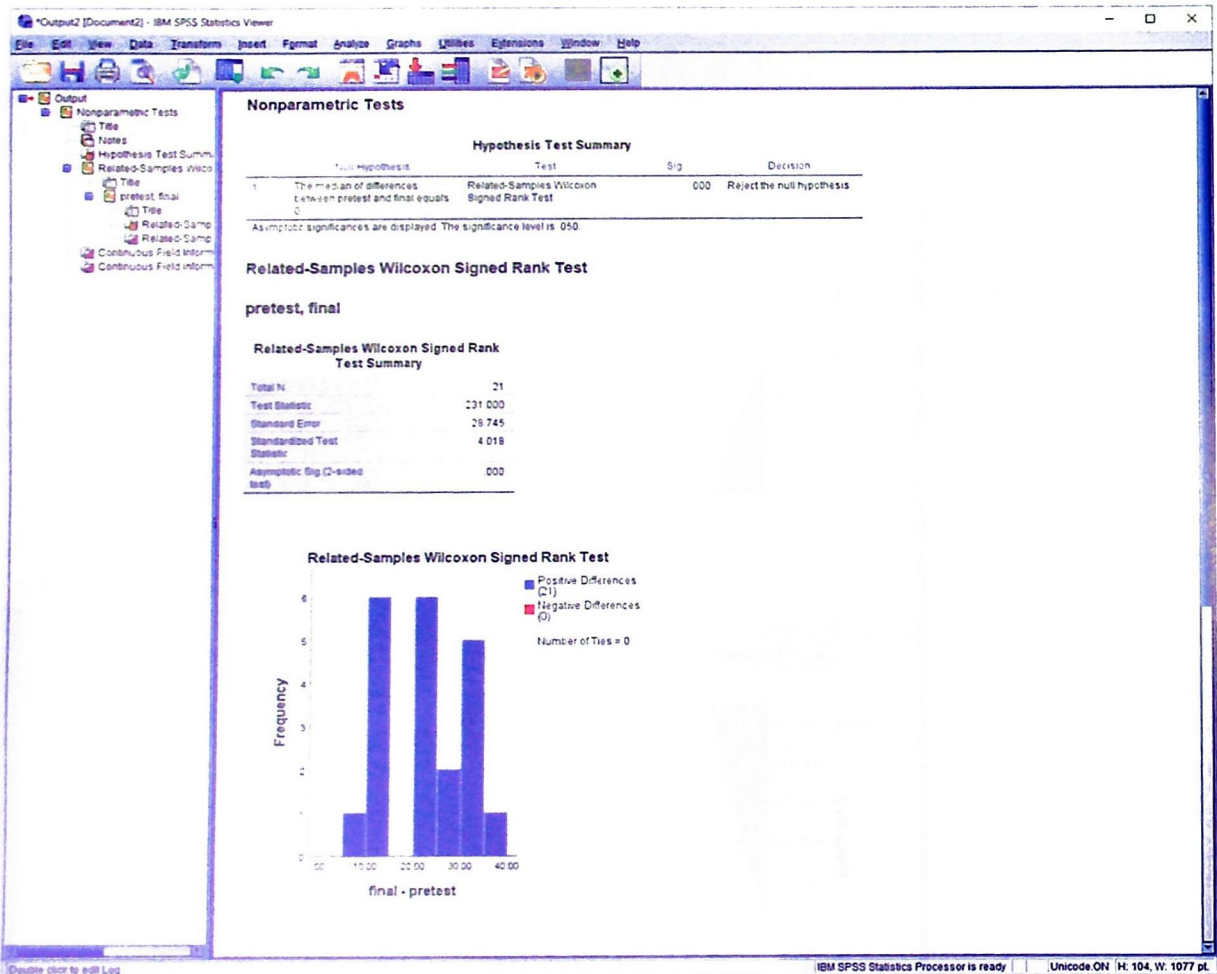




The example above shows that no significant difference was found between the results of the long-distance and medium-distance races.

Phrasing Results That Are Significant

A significant result means that a change has occurred between the two measurements. If we compared PRETEST to FINAL scores using the GRADES.sav dataset we would obtain:



A Wilcoxon test examined the results of the pretest and final exam scores. A significant difference was found in the results ($Z = 4.018$, $p < .05$). Final exam scores were better than pretest scores.

Phrasing Results That Are Not Significant

In fact, the results in the original example were not significant, so we could state the following:

A Wilcoxon test examined the results of the medium-distance and long-distance races. No significant difference was found in the results ($Z = .085$, $p > .05$). Medium-distance results were not significantly different from long-distance results.

Practice Exercise

Use the RACE.sav data file to determine whether or not the outcome of short-distance races is different from that of medium-distance races. Phrase your results.

Section 8.5 Kruskal-Wallis H Test

Description

The Kruskal-Wallis H test is the nonparametric equivalent of the one-way ANOVA. It tests whether or not several independent samples come from the same population.

Assumptions

Because the test is nonparametric, there are very few assumptions. However, the test does assume an **ordinal** level of measurement for the **dependent variable**. The **independent variable** should be **nominal** or **ordinal**.

SPSS Data Format

SPSS requires one variable to represent the **dependent variable** and another to represent the levels of the **independent variable**. The **dependent variable** must be entered as a scale-type variable even if it is actually **ordinal**.

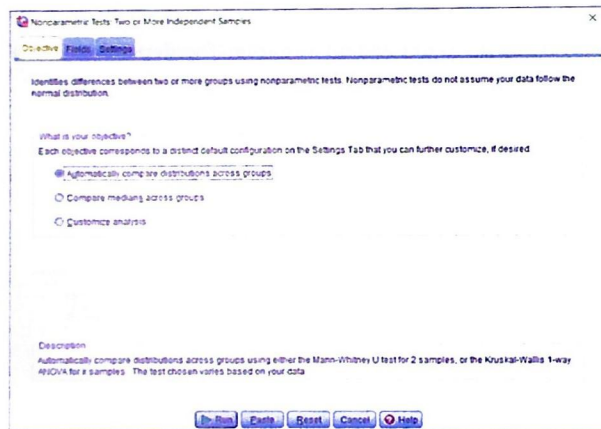
Running the Command

	long	medium	short	experience	var	var	var
1	1.00	4.00	6.00	2.00			
2	2.00	3.00	4.00	2.00			
3	3.00	2.00	7.00	2.00			
4	4.00	5.00	3.00	2.00			
5	5.00	1.00	10.00	1.00			
6	6.00	8.00	5.00	1.00			
7	7.00	7.00	12.00	1.00			
8	8.00	6.00	1.00	1.00			
9	9.00	10.00	3.00	.00			
10	10.00	9.00	9.00	.00			
11	11.00	11.00	11.00	.00			
12	12.00	12.00	2.00	.00			
13							

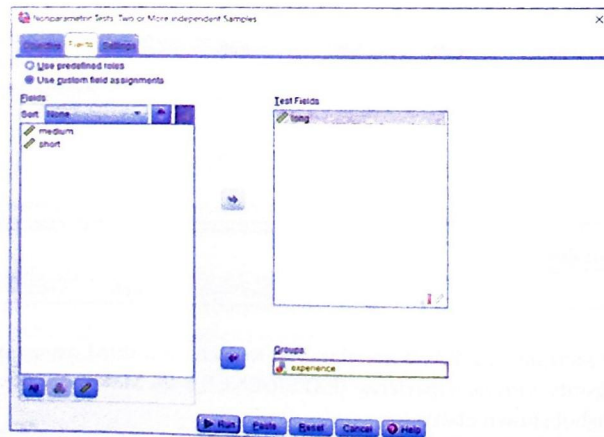
This example modifies the RACE.sav data file to include a third group of four additional participants with no experience (EXPERIENCE = 0). Make sure your data look like the screenshot shown above.



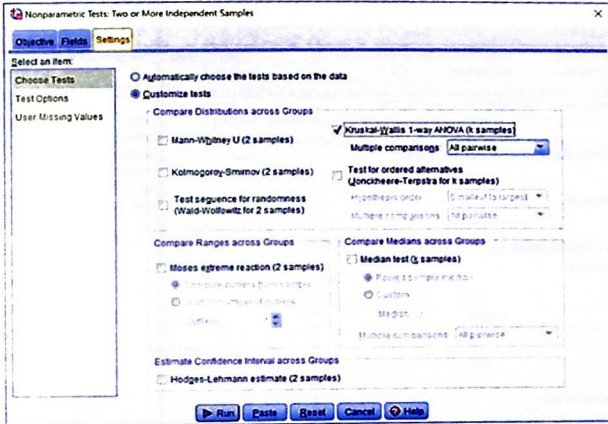
To run the command, click *Analyze*, then *Nonparametric Tests*, then *Independent Samples*. This will bring up the main dialog box, below.



Leave the *Objective* the same and click the *Fields* tab. Move *LONG* to the *Test Fields* area and *EXPERIENCE* to the *Groups* area.



Select the *Settings* tab and *Customize tests* to select *Kruskal-Wallis 1-way ANOVA*. Also, select *Multiple comparisons* and choose *All pairwise*. Just as post-hoc tests are necessary with parametric one-way ANOVA, they are also necessary with nonparametric versions. This step will have SPSS compute them for us. Click *Run* to perform the analysis.



Reading the Output

The output will consist of the real-language Output. Here, it tells us that the distribution of the variable LONG is the same across all levels of EXPERIENCE.

IBM SPSS Statistics Processor is ready | Unicode ON | H: 22, W: 895 pt

*Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Log
- Nonparametric Tests
 - Title
 - Notes
 - Hypothesis Test Summary
 - Independent-Samples Kruskal-Wallis Test
 - Title
 - long across experience
 - Title
 - Independent-Samples Kruskal-Wallis Test Summary
 - Independent-Samples Kruskal-Wallis Test
 - Pairwise Comparisons
 - Pairwise Comparisons
 - Continuous Field Information
 - Categorical Field Information

Nonparametric Tests

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of long is the same across categories of experience	Independent-Samples Kruskal-Wallis Test	.007	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .050

Independent-Samples Kruskal-Wallis Test

long across experience

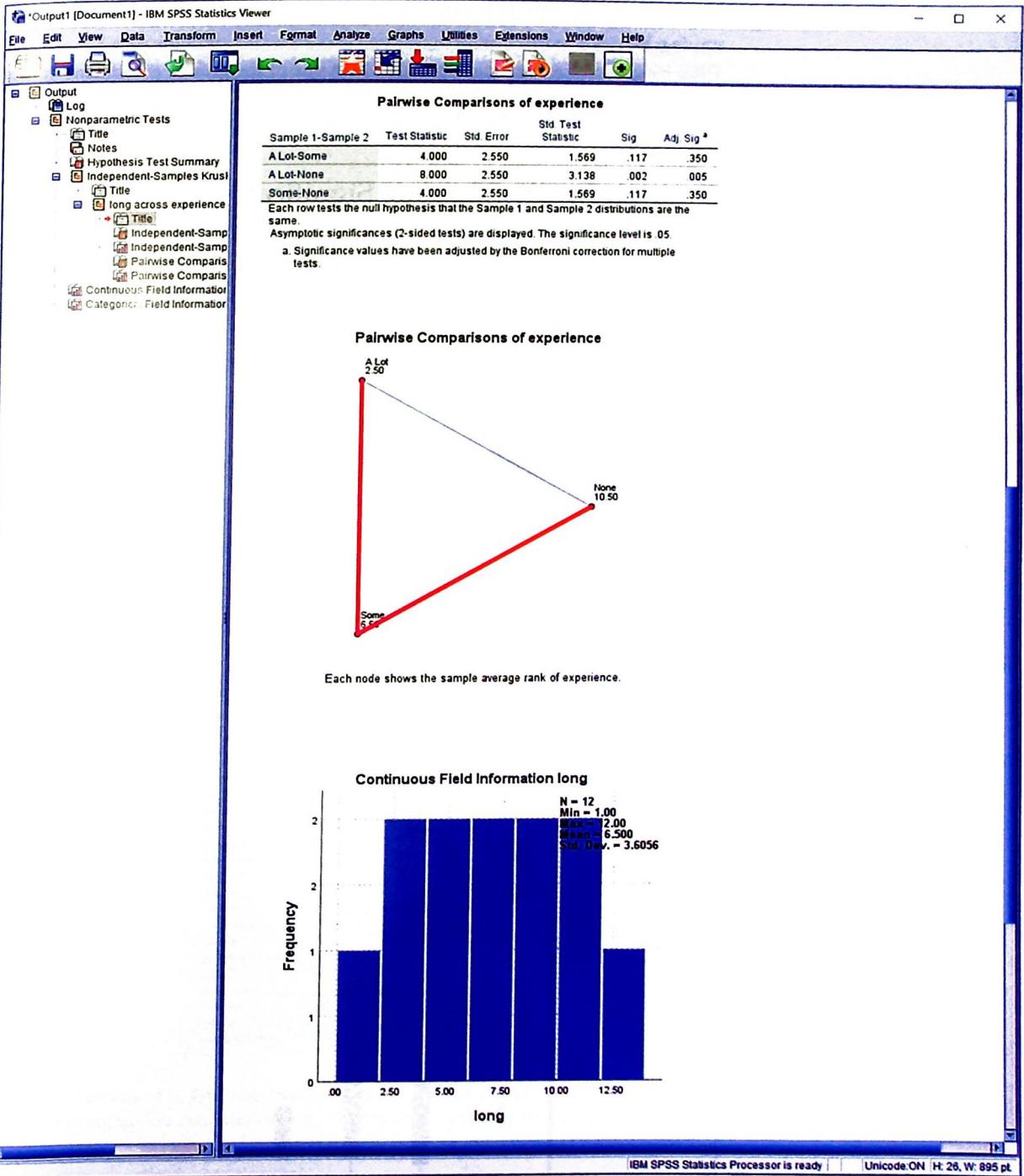
Independent-Samples Kruskal-Wallis Test Summary

Total N	12
Test Statistic	9.846 ^a
Degree Of Freedom	2
Asymptotic Sig. (2-sided test)	.007

^a The test statistic is adjusted for ties

Independent-Samples Kruskal-Wallis Test

The box plot displays the distribution of the variable 'long' across three categories of experience: 'None', 'Some', and 'A Lot'. The y-axis is labeled 'long' and ranges from 0.00 to 12.00. The 'None' group shows a median around 10.5, with a box from approximately 9.5 to 11.5 and whiskers extending from 9.0 to 12.0. The 'Some' group has a median around 6.5, with a box from 5.5 to 7.5 and whiskers from 5.0 to 8.0. The 'A Lot' group has a median around 2.5, with a box from 1.5 to 3.5 and whiskers from 1.0 to 4.0.



The Pairwise Comparisons of experience table shows that EXPERIENCE 2 (Experienced) is significantly different from EXPERIENCE 0 (None). However, the other two comparisons are not significantly different from each other.

Drawing Conclusions

Like the one-way ANOVA, the Kruskal-Wallis test assumes that the groups are equal. Thus, a significant result indicates that at least one of the groups is different from at least one other group. The *Pairwise Comparisons* command will allow us to determine which groups are different.

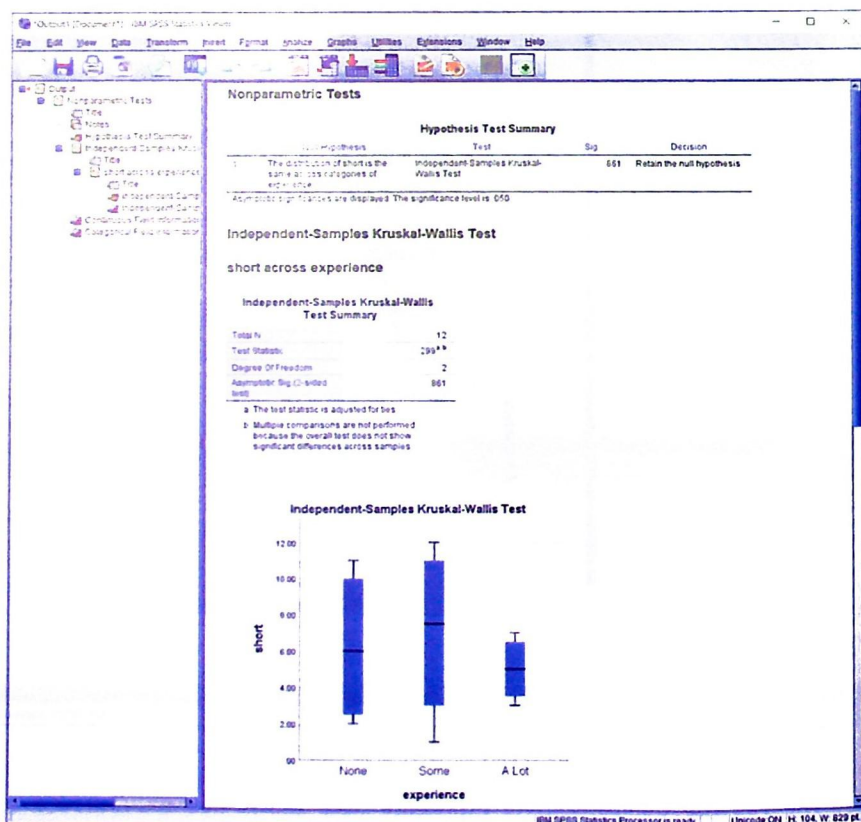
Phrasing Results That Are Significant

The preceding example is significant, so we could state the following:

A Kruskal-Wallis test was conducted comparing the outcome of a long-distance race for runners with varying levels of experience. A significant result was found ($H(2) = 9.846, p < .01$), indicating that the groups differed from each other. Follow-up pairwise comparisons indicated that runners with the greatest experience performed significantly better than runners with no experience.

Phrasing Results That Are Not Significant

If we conducted the analysis using the results of the short-distance race, we would get the following output, which is not significant.



This result is not significant, so we could state the following:

A Kruskal-Wallis test was conducted comparing the outcome of a short-distance race for runners with varying levels of experience. No significant difference was found ($H(2) = 0.299, p > .05$), indicating that the groups did not differ significantly from each other. Experience did not seem to influence the results of the short-distance race.

Section 8.6 Friedman Test

Description

The Friedman test is the nonparametric equivalent of a one-way repeated-measures ANOVA. It is used when you have more than two measurements from related participants.

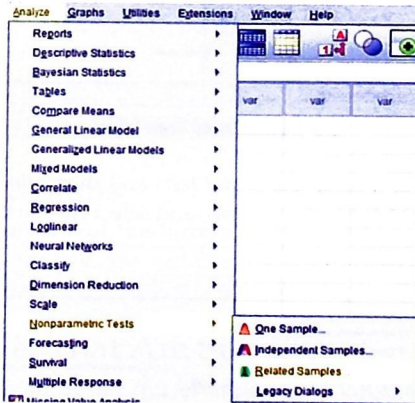
Assumptions

The test uses the rankings of the variables, so the data must at least be **ordinal**. No other assumptions are required.

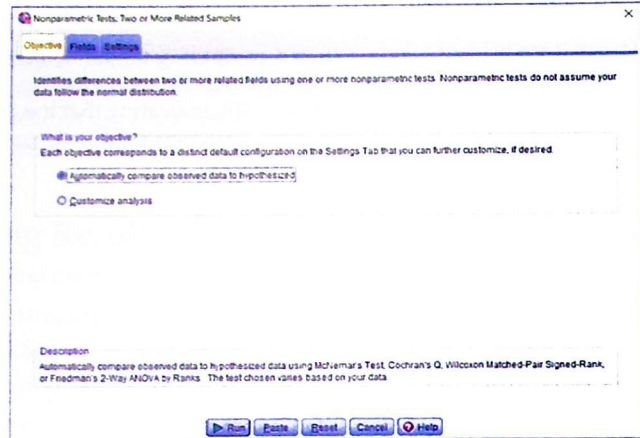
SPSS Data Format

SPSS requires at least three variables in the SPSS data file. Each variable represents the **dependent variable** at one of the levels of the **independent variable**.

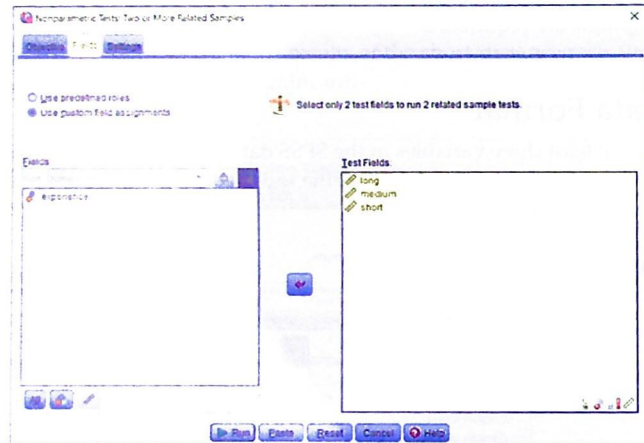
Running the Command



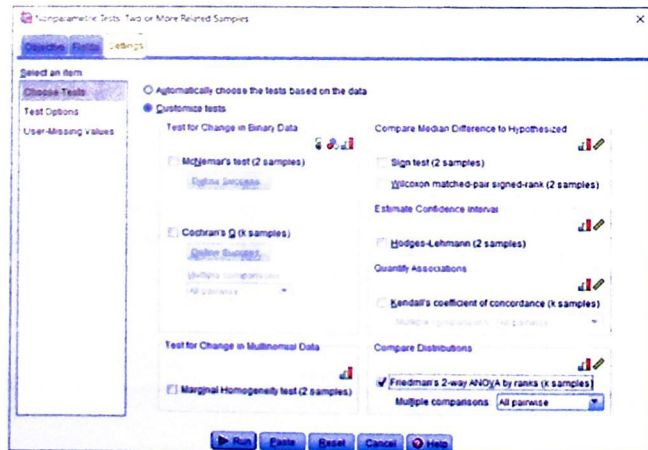
Locate the command by clicking *Analyze*, then *Nonparametric Tests*, then *Related Samples*. This will bring up the main dialog box. This example uses the RACE.sav data file.



Leave the *Objective* the same, and select the *Fields* tab. Move all three variables representing race places over to the *Test Fields* area (LONG, MEDIUM, SHORT).

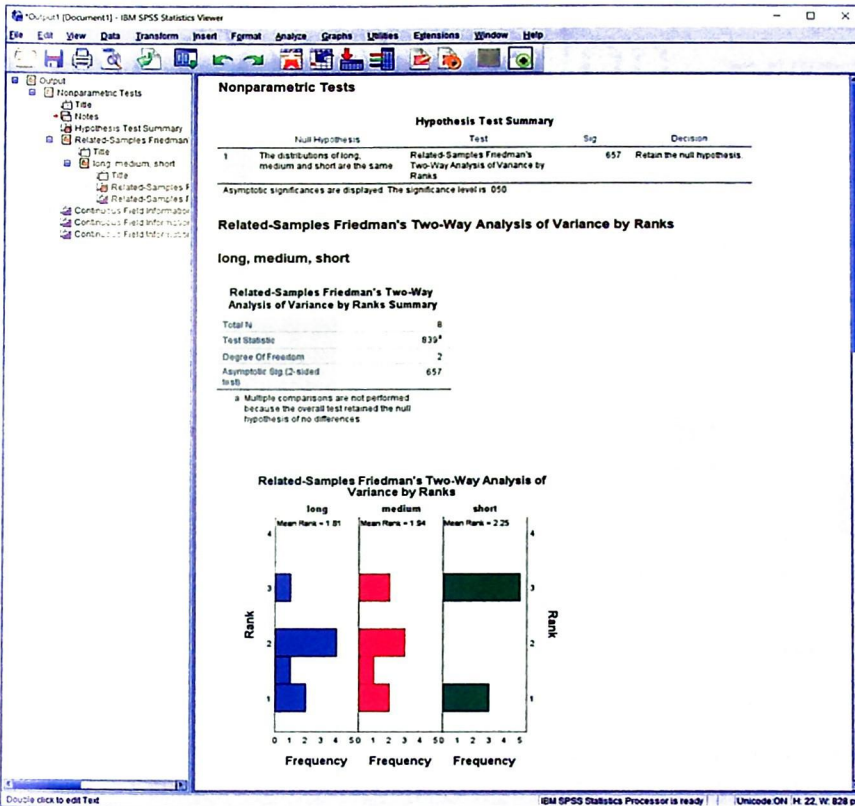


Under the *Settings* tab, select *Customize tests* and then select the *Friedman's 2-way ANOVA by ranks*. Select *Multiple comparisons*, and select *All pairwise*. Run the test.



Reading the Output

The real-language Model Viewer will tell us that there was not a significant difference in the distributions of the three variables.



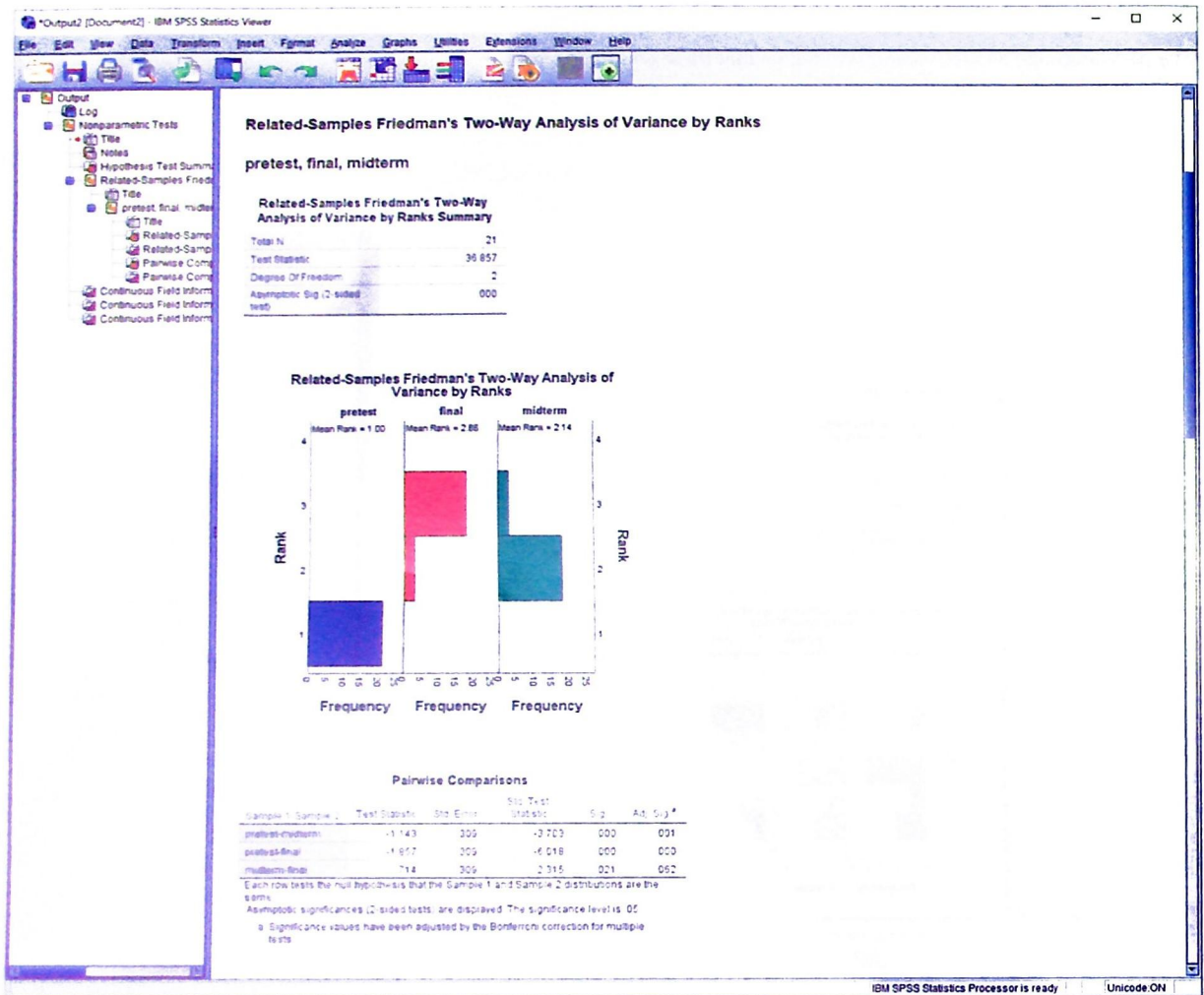
Drawing Conclusions

The Friedman test assumes that the three variables are from the same population. A significant value indicates that the variables are not equivalent.

Phrasing Results That Are Significant

If we obtained a significant result (for example using GRADES.sav and comparing PRETEST, MIDTERM, and FINAL), we could state the following:

A Friedman test was conducted comparing the average scores on Pretest, Midterm, and Final exams. A significant difference was found ($\chi^2(2) = 36.857, p < .05$). Scores significantly changed over the course of the semester.



Phrasing Results That Are Not Significant

In fact, our example was not significant, so we could state the following:

A Friedman test was conducted comparing the average place in a race of runners for short-distance, medium-distance, and long-distance races. No significant difference was found ($\chi^2(2) = 0.839, p > .05$). The length of the race did not significantly affect the results of the race.

Practice Exercise

Use the data in Practice Dataset 3 in Appendix B. If anxiety is measured on an **ordinal scale**, determine if anxiety levels changed over time. Phrase your results.

Chapter 9

Test Construction

Section 9.1 Item-Total Analysis

Description

Item-total analysis is a way to assess the **internal consistency** of a dataset. As such, it is one of many tests of **reliability**. Item-total analysis comprises a number of items that make up a scale or a test designed to measure a single construct (e.g., intelligence), and it determines the degree to which all of the items measure the same construct. It does not tell you if it is measuring the correct construct (that is a question of **validity**). Before a test can be valid, however, it must first be reliable.

Assumptions

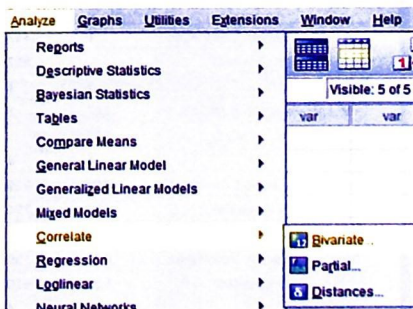
All the items in the scale should be measured on an **interval** or **ratio scale**. In addition, each item should be normally distributed. If your items are **ordinal** in nature, you can conduct the analysis using the Spearman *rho* correlation instead of the Pearson *r* correlation.

SPSS Data Format

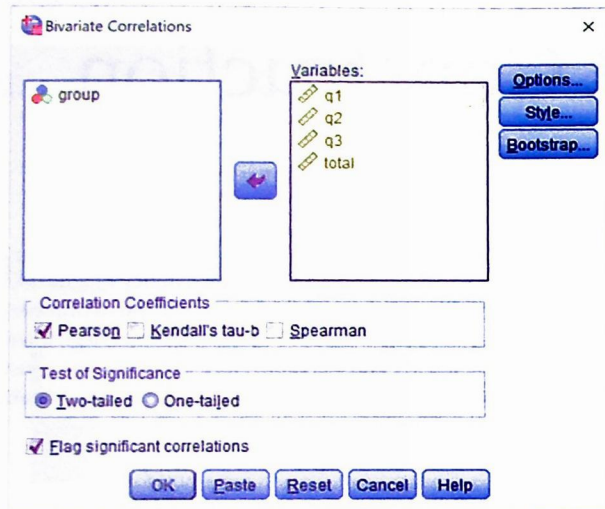
SPSS requires one variable for each item (or question) in the scale. In addition, you must have a variable representing the total score for the scale.

Conducting the Test

Item-total analysis uses the *Pearson Correlation* command. To conduct it, open the QUESTIONS.sav data file you created in Chapter 2. Click *Analyze*, then *Correlate*, then *Bivariate*.



Place all questions and the total in the right-hand window, and click **OK**. (For more help on conducting correlations, see Chapter 5.) The total can be calculated with the techniques discussed in Chapter 2.



Reading the Output

The output consists of a correlation matrix containing all questions and the total. Use the column labeled **TOTAL**, and locate the correlation between the total score and each question. In the example shown to the right, **QUESTION 1** has a correlation of 0.873 with the total score. **QUESTION 2** has a correlation of $-.130$ with the total score. **QUESTION 3** has a correlation of $.926$ with the total score.

Correlations

		q1	q2	q3	total
q1	Pearson Correlation	1	-.447	.718	.873
	Sig. (2-tailed)		.553	.282	.127
	N	4	4	4	4
q2	Pearson Correlation	-.447	1	-.229	-.130
	Sig. (2-tailed)	.553		.771	.870
	N	4	4	4	4
q3	Pearson Correlation	.718	-.229	1	.926
	Sig. (2-tailed)	.282	.771		.074
	N	4	4	4	4
total	Pearson Correlation	.873	-.130	.926	1
	Sig. (2-tailed)	.127	.870	.074	
	N	4	4	4	4

IBM SPSS Statistics Processor is ready Unicode ON H: 244, W: 885 pt

Interpreting the Output

Item-total correlations should always be positive. If you obtain a negative correlation, that question should be removed from the scale (or you may consider whether it should be reverse-keyed).

Generally, item-total correlations of greater than .7 are considered desirable. Those of less than .3 are considered weak. Any questions with correlations of less than .3 should be removed from the scale.

Normally, the worst question is removed, and then the total is recalculated. After the total is recalculated, the item-total analysis is repeated without the question that was removed. Then, if any questions have correlations of less than .3, the worst one is removed, and the process is repeated.

When all remaining correlations are greater than .3, the remaining items in the scale are considered to be those that are internally consistent.

Section 9.2 Cronbach's Alpha

Description

Cronbach's alpha is a measure of **internal consistency**. As such, it is one of many tests of **reliability**. Cronbach's alpha comprises a number of items that make up a scale designed to measure a single construct (e.g., intelligence), and it determines the degree to which all the items are measuring the same construct. It does not tell you if it is measuring the correct construct (that is a question of **validity**). As stated earlier, before a test can be valid, it must first be reliable.

Assumptions

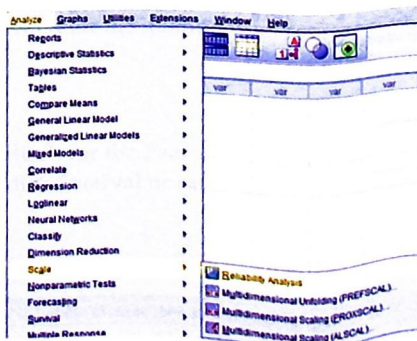
All the items in the scale should be measured on an **interval or ratio scale**. In addition, each item should be normally distributed.

SPSS Data Format

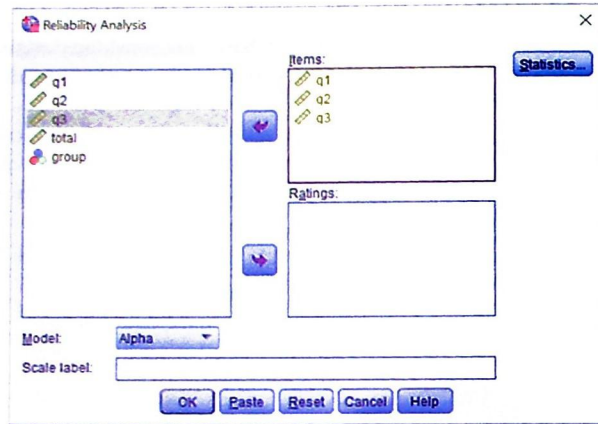
SPSS requires one variable for each item (or question) in the scale.

Running the Command

We will continue to use the `QUESTIONS.sav` data file we first created in Chapter 2. Click *Analyze*, then *Scale*, then *Reliability Analysis*.



This will bring up the main dialog box for Reliability Analysis. Transfer the questions from your scale to the *Items* blank, and click *OK*. Do not transfer any variables representing total scores.



Note that if you change the options under *Model*, additional measures of internal consistency (e.g., split-half) can be calculated.

Reading the Output

In this example, the reliability coefficient is .407. Numbers close to 1 are very good, but numbers close to 0 represent poor **internal consistency**.

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	4	100.0
	Excluded ^a	0	0
	Total	4	100.0

^a Listwise deletion based on all variables in the procedure

Reliability Statistics

Cronbach's		N of Items
Alpha		
.407		3

IBM SPSS Statistics Processor is ready | Unicode:ON | H: 84, W: 460 pt.

Section 9.3 Test-Retest Reliability

Description

Test-retest reliability is a measure of **temporal stability**. As such, it is a measure of **reliability**. Unlike measures of **internal consistency** that tell you the extent to which all of the questions that make up a scale measure the same construct, measures of **temporal stability** tell you whether or not the instrument is consistent over time or over multiple administrations.

Assumptions

The total score for the scale should be an **interval** or **ratio scale**. The scale scores should be normally distributed.

SPSS Data Format

SPSS requires a variable representing the total score for the scale at the time of first administration. A second variable representing the total score for the same participants at a different time (normally two weeks later) is also required.

Running the Command

The test-retest reliability coefficient is simply a Pearson correlation coefficient for the relationship between the total scores for the two administrations. To compute the coefficient, follow the directions for computing a Pearson correlation coefficient (Chapter 5, Section 5.1). Use the two variables representing the two administrations of the test.

Reading the Output

The correlation between the two scores is the test-retest reliability coefficient. It should be positive. Strong **reliability** is indicated by values close to 1. Weak **reliability** is indicated by values close to 0.

Section 9.4 Criterion-Related Validity

Description

Criterion-related validity determines the extent to which the scale you are testing correlates with a criterion. For instance, *ACT* scores should correlate highly with GPA. If they do, that is a measure of **validity** for *ACT* scores. If they do not, that indicates that *ACT* scores may not be valid for the intended purpose.

Assumptions

All of the same assumptions for the Pearson correlation coefficient apply to measures of criterion-related validity (**interval** or **ratio scales**, **normal distribution**, etc.).

SPSS Data Format

Two variables are required. One variable represents the total score for the scale you are testing. The other represents the criterion you are testing it against.

Running the Command

Calculating criterion-related validity involves determining the Pearson correlation value between the scale and the criterion. See Chapter 5, Section 5.1 for complete information.

Reading the Output

The correlation between the two scores is the criterion-related validity coefficient. It should be positive. Strong **validity** is indicated by values close to 1. Weak **validity** is indicated by values close to 0.

Section 9.5 Inter-Rater Reliability

Description

There are many ways to measure inter-rater reliability. It can be as simple as the correlation between two reviewer's scores if you have an interval or ratio scale (or even a Spearman *rho* if you have a nominal scale). A common measure with nominal scales, however, is Cohen's Kappa.

Assumptions

Cohen's Kappa works best with nominal scales with a limited number of categories.

SPSS Data Format

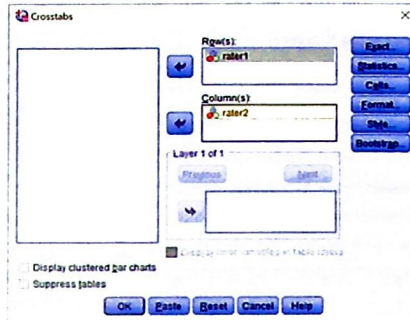
Two variables are required. One variable represents the rating of one person and the second variable represents the rating of the other rater. For example, you could have a datafile using the data presented here.

The screenshot shows the IBM SPSS Statistics Data Editor window. The title bar reads '*Untitled2 [DataSet3] - IBM SPSS Statistics Data Editor'. The menu bar includes File, Edit, View, Data, Transform, Analyze, Graphs, Utilities, Extensions, Window, and Help. The toolbar contains various icons for file operations and analysis. The data grid shows two variables, 'rater1' and 'rater2', with 10 rows of data. The status bar at the bottom indicates 'IBM SPSS Statistics Processor is ready' and 'Unicode: ON'.

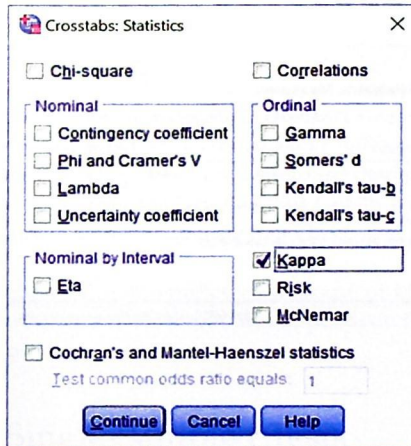
	rater1	rater2	var	var	var	var
1	7 00	7 00				
2	8 00	8 00				
3	4 00	3 00				
4	5 00	5 00				
5	6 00	6 00				
6	4 00	5 00				
7	5 00	5 00				
8	8 00	8 00				
9	3 00	2 00				
10	1 00	1 00				
11						

Running the Command

Calculating inter-rater reliability involves the crosstabs command. See Chapter 3, Section 3.2 for more information. Enter one rater's scores as the columns and the other rater's scores as the rows.



When running crosstabs, you select the *Statistics* option and then select *Kappa*.



Reading the Output

The inter-rater reliability is represented at the bottom of the output as Kappa. In the example here, Kappa is equal to .651. While there is some disagreement on interpreting Kappa, Landis and Koch (1977) have suggested values < .2 as slight, .2-.4 as fair, .4-.6 as moderate, .5-.8 as strong, and > .8 as almost perfect.

*Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Crosstabs
 - Title
 - Notes
 - Case Processing Summary
 - rater1 * rater2 Crosstabulation
 - Symmetric Measures

Crosstabs

Case Processing Summary

	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
rater1 * rater2	10	100.0%	0	0.0%	10	100.0%

rater1 * rater2 Crosstabulation

Count

		rater2							Total
		1.00	2.00	3.00	5.00	6.00	7.00	8.00	
rater1	1.00	1	0	0	0	0	0	0	1
	3.00	0	1	0	0	0	0	0	1
	4.00	0	0	1	1	0	0	0	2
	5.00	0	0	0	2	0	0	0	2
	6.00	0	0	0	0	1	0	0	1
	7.00	0	0	0	0	0	1	0	1
	8.00	0	0	0	0	0	0	2	2
	Total	1	1	1	3	1	1	2	10

Symmetric Measures

Measure of Agreement	Kappa	Value	Asymptotic Standard Error ^a	Approximate T ^b	Approximate Significance
		.651	.157	5.449	.000
N of Valid Cases		10			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.

IBM SPSS Statistics Processor is ready | Unicode ON | H: 22, W: 656 pt

Appendix A

Effect Size

Many disciplines are placing increased emphasis on reporting **effect size**. While statistical hypothesis testing provides a way to tell the odds that differences are real, effect sizes provide a way to judge the relative importance of those differences. That is, they tell us the size of the difference or relationship. They are also critical if you would like to estimate necessary sample sizes, conduct a power analysis, or conduct a meta-analysis. Many professional organizations (e.g., the American Psychological Association) are now requiring or strongly suggesting that effect sizes be reported in addition to the results of hypothesis tests.

Because there are at least 41 different types of effect sizes,¹ each with somewhat different properties, the purpose of this appendix is not to be a comprehensive resource on **effect size**, but rather to show you how to calculate some of the most common measures of **effect size** using SPSS.

Section A.1 Cohen's *d*

One of the simplest and most popular measures of **effect size** is **Cohen's *d***. **Cohen's *d*** is a member of a class of measurements called *standardized mean differences*. In essence, *d* is the difference between the two means divided by the overall **standard deviation**.

It is not only a popular measure of **effect size**, but Cohen has also suggested a simple basis to interpret the value obtained. Cohen² suggests that effect sizes of .2 are small, .5 are medium, and .8 are large.

We will discuss **Cohen's *d*** as the preferred measure of **effect size** for *t* tests. Unfortunately, SPSS does not calculate **Cohen's *d***. However, this appendix will cover how to calculate it from the output that SPSS does produce.

Effect Size for Single-Sample *t* Tests

Although SPSS does not calculate **effect size** for the single-sample *t* test, calculating **Cohen's *d*** is a simple matter.

Cohen's *d* for a single-sample *t* test is equal to the **mean** difference over the **standard deviation**. If SPSS provides us with the following output (testing whether HEIGHT in the HEIGHT.SAV datafile is equal to 69.5 inches), we calculate *d* as follows.

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
HEIGHT	16	66.9375	3.90672	.97668

One-Sample Test

Test Value = 69.5

95% Confidence Interval of the Difference

	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
HEIGHT	-2.624	15	.019	-2.56250	-4.6442	-.4808

IBM SPSS Statistics Processor is ready | Unicode ON | H: 104, W: 752 pt.

$$d = \frac{\bar{D}}{s_D}$$

$$d = \frac{-2.5625}{3.907}$$

$$d = .656$$

In this example, using Cohen's guidelines to judge **effect size**, we would have an **effect size** between medium and large.

Effect Size for Independent-Samples *t* Tests

Calculating **effect size** from the independent *t* test output is a little more complex because SPSS does not provide us with the **pooled standard deviation**. The upper section of the output, however, does provide us with the information we need to calculate it. The output presented here is the same output we worked with in Chapter 6 (Using SAMPLE.sav and seeing if GRADE is different for the two groups of MORNING).

T-Test

Group Statistics

Are you a morning person?	N	Mean	Std. Deviation	Std. Error Mean
GRADE No	2	82.5000	3.53553	2.50000
Yes	2	78.0000	7.07107	5.00000

Independent Samples Test

Levene's Test for Equality of Variances

T-test for Equality of Means

GRADE		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
GRADE	Equal variances assumed			805	2	.505	4.50000	5.59017	-19.55256	28.55256
	Equal variances not assumed			805	1.471	.530	4.50000	5.59017	-30.09261	39.09261

IBM SPSS Statistics Processor is ready | Unicode ON | H: 564, W: 733 pt.

$$S_{pooled} = \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}$$

$$S_{pooled} = \sqrt{\frac{(2 - 1)3.5355^2 + (2 - 1)0.711^2}{2 + 2 - 2}}$$

$$S_{pooled} = \sqrt{\frac{62.500}{2}}$$

$$S_{pooled} = 5.59$$

Once we have calculated the **pooled standard deviation** (s_{pooled}), we can calculate Cohen's d .

$$d = \frac{\bar{X}_1 - \bar{X}_2}{S_{pooled}}$$

$$d = \frac{82.50 - 78.00}{5.59}$$

$$d = .81$$

So, in this example, using Cohen's guidelines for the interpretation of d , we would have obtained a large effect size.

Effect Size for Paired-Samples t Tests

As you have probably learned in your statistics class, a paired-samples t test is really just a special case of the single-sample t test. Therefore, the procedure for calculating Cohen's d is also the same. The SPSS output, however, looks a little different, so you will be taking your values from different areas. This example uses GRADES.sav.

The screenshot shows the IBM SPSS Statistics Viewer window with the following output:

T-Test

Paired Samples Statistics

	Mean	N	Std. Deviation	Std. Error Mean
Pair 1 pretest	63.3333	21	8.92935	1.94854
final	86.0000	21	9.61249	2.09762

Paired Samples Correlations

	N	Correlation	Sig.
Pair 1 pretest & final	21	.509	.019

Paired Samples Test

Paired Differences

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference			t	df	Sig. (2-tailed)
					Mean	Lower	Upper			
Pair 1	pretest - final	-22.66667	9.21050	2.00990	-26.85924	-18.47410	-11.278	20	.000	

$$d = \frac{\bar{D}}{S_D}$$

$$d = \frac{-22.6667}{9.2105}$$

$$d = 2.46$$

Notice that in this example, we represent the **effect size** (d) as a positive number even though it is negative. Effect sizes are always positive numbers. In this example, using Cohen's guidelines for the interpretation of d , we have found a very large **effect size**.

Section A.2 r^2 (Coefficient of Determination)

While Cohen's d is the appropriate measure of **effect size** for t tests, correlation and regression effect sizes should be determined by squaring the correlation coefficient. This squared correlation is called the **coefficient of determination**. Cohen³ suggested that correlations of .5, .3, and .1 corresponded to large, moderate, and small relationships. Those values squared yield **coefficients of determination** of .25, .09, and .01, respectively. It would appear, therefore, that Cohen is suggesting that accounting for 25 percent of the variability represents a large effect, 9 percent a moderate effect, and 1 percent a small effect.

Effect Size for Correlation

Nowhere is the effect of sample size on statistical power (and therefore **significance**) more apparent than with correlations. Given a large enough sample, *any* correlation can become significant. Thus, **effect size** becomes critically important in the interpretation of correlations.

The standard measure of **effect size** for correlations is the **coefficient of determination** (r^2) previously discussed. The coefficient should be interpreted as the proportion of **variance** in the **dependent variable** that can be accounted for by the relationship between the **independent** and **dependent variables**. While Cohen provided useful guidelines for interpretation, each problem should be interpreted in terms of its true **practical significance**. For instance, if a treatment is very expensive to implement, or has significant side effects, then a larger correlation should be required before the relationship becomes important. For treatments that are very inexpensive, a much smaller correlation can be considered important.

To calculate the **coefficient of determination**, simply take the r value that SPSS provides and square it.

Effect Size for Regression

The Model Summary section of the output reports R^2 for you. The example output here (from the HEIGHT.sav dataset for a regression to predict WEIGHT from HEIGHT) shows a **coefficient of determination** of .649, meaning that almost 65 percent (.649) of the **variability in the dependent variable** is accounted for by the relationship between the **dependent** and **independent variables**.

Regression

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	HEIGHT ^b		Enter

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

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.806 ^a	.649	.624	16.14801

a. Predictors: (Constant), HEIGHT

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6760.323	1	6760.323	25.926	.000 ^b
	Residual	3650.614	14	260.758		
	Total	10410.938	15			

a. Dependent Variable: WEIGHT
b. Predictors: (Constant), HEIGHT

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.
		B	Std. Error	Beta	t	
1	(Constant)	-234.681	71.552		-3.280	.005
	HEIGHT	5.434	1.067	.806	5.092	.000

a. Dependent Variable: WEIGHT

Section A.3 Eta Squared (η^2)

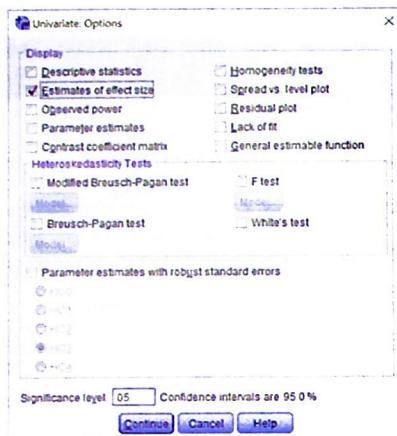
A third measure of effect size is **Eta Squared (η^2)**. **Eta Squared** is used for Analysis of Variance models. The *GLM* (General Linear Model) function in SPSS (the function that runs the procedures under *Analyze—General Linear Model*) will provide **Eta Squared (η^2)**.

$$\eta^2 = \frac{SS_{effect}}{SS_{effect} + SS_{error}}$$

Eta Squared has an interpretation similar to a squared correlation coefficient (r^2). It represents the proportion of the **variance** accounted for by the effect. Unlike r^2 , however, which represents only linear relationships, η^2 can represent any type of relationship.

Effect Size for Analysis of Variance

For most Analysis of Variance problems, you should elect to report **Eta Squared** as your **effect size** measure. SPSS provides this calculation for you as part of the *General Linear Model (GLM)* command. To obtain **Eta Squared**, simply click on the *Options* box in the main **dialog box** for the *GLM* command you are running (this works for Univariate, Multivariate, and Repeated Measures versions of the command even though only the Univariate option is presented here).



Once you have selected *Options*, a new dialog box will appear. One of the options in that box will be *Estimates of effect size*. When you select that box, SPSS will provide **Eta Squared** values as part of your output.

The example here uses the *GRADES.sav* dataset and ANOVA on *FINAL* grades and *INSTRUCT*.

Univariate Analysis of Variance

Between-Subjects Factors

	instruct	n
	1.00	7
	2.00	7
	3.00	7

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model ^a	619.714 ^a	2	309.857	4.541	.025	.335
Intercept	155316.000	1	155316.000	2276.089	.000	.992
instruct	619.714	2	309.857	4.541	.025	.335
Error	1228.286	18	68.238			
Total	157164.000	21				
Corrected Total	1848.000	20				

^a R Squared = .335 (Adjusted R Squared = .261)

In the above example, we obtained an **Eta Squared** of .335 for our main effect for *Instructor*. Because we interpret **Eta Squared** using the same guidelines as r^2 , we would conclude that this represents a large effect size for *instructor* ($> .25$).

Appendix B

Practice Exercise Data Sets

The practice exercises given throughout the text use a variety of data. Some practice exercises use the datasets shown in the examples. Others use longer datasets. The longer datasets are presented here.

Practice Dataset 1

You have conducted a study in which you collected data from 23 participants. You asked each subject to indicate his or her sex (SEX), age (AGE), and marital status (MARITAL). You gave each subject a test to measure mathematics skills (SKILL), where the higher scores indicated a higher skill level. The data are presented below. Note that you will have to code the variables SEX and MARITAL and also indicate that they are measured on a nominal scale.

This example assumes students code SEX as 1 = M, 2 = F and MARITAL as 1 = Single, 2 = Married, 3 = Divorced.

SEX	AGE	MARITAL	SKILL
M	23	Single	34
F	35	Married	40
F	40	Divorced	38
M	19	Single	20
M	28	Married	30
F	35	Divorced	40
F	20	Single	38
F	29	Single	47
M	29	Married	26
M	40	Married	24
F	24	Single	45
M	23	Single	37
F	18	Single	44
M	21	Single	38
M	50	Divorced	32
F	25	Single	29
F	20	Single	38
M	24	Single	19
F	37	Married	29
M	42	Married	42
M	35	Married	59
M	23	Single	45
F	40	Divorced	20

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	SEX	Numeric	8	2		(1 00, Male)	None	8	Right	Nominal	Input
2	AGE	Numeric	8	2		None	None	8	Right	Scale	Input
3	MARITAL	Numeric	8	2		(1 00, Singl...)	None	8	Right	Nominal	Input
4	SKILL	Numeric	8	2		None	None	8	Right	Scale	Input
5											

Practice Dataset 2

A survey of employees is conducted. Each employee provides the following information: Salary (SALARY), Years of Service (YOS), Sex (SEX), Job Classification (CLASSIFY), and Education Level (EDUC). Note that you will have to code SEX (Male = 1, Female = 2) and CLASSIFY (Clerical = 1, Technical = 2, Professional = 3), and indicate that they are measured on a **nominal scale**.

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	SALARY	Numeric	8	2		None	None	8	Right	Scale	Input
2	YOS	Numeric	8	2		None	None	8	Right	Scale	Input
3	SEX	Numeric	8	2		(1 00, Male)	None	8	Right	Nominal	Input
4	CLASSIFY	Numeric	8	2		(1 00, Clerc...	None	8	Right	Nominal	Input
5	EDUC	Numeric	8	2		None	None	8	Right	Scale	Input

SALARY	YOS	SEX	CLASSIFY	EDUC
35,000	8	Male	Technical	14
18,000	4	Female	Clerical	10
20,000	1	Male	Professional	16
50,000	20	Female	Professional	16
38,000	6	Male	Professional	20
20,000	6	Female	Clerical	12
75,000	17	Male	Professional	20
40,000	4	Female	Technical	12
30,000	8	Male	Technical	14
22,000	15	Female	Clerical	12
23,000	16	Male	Clerical	12
45,000	2	Female	Professional	16

Practice Dataset 3

Participants who have phobias are given one of three treatments (CONDITION). Their anxiety level (1 to 10) is measured at three intervals—before treatment (ANXPRES), one hour after treatment (ANX1HR), and again four hours after treatment (ANX4HR). Note that you will have to code the variable CONDITION and indicate that they are measured on a **nominal scale**.

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	ANXPRES	Numeric	8	2		None	None	8	Right	Scale	Input
2	ANX1HR	Numeric	8	2		None	None	8	Right	Scale	Input
3	ANX4HR	Numeric	8	2		None	None	8	Right	Scale	Input
4	CONDIT	Numeric	8	2		{1.00, Place...	None	8	Right	Nominal	Input
5											

ANXPRES	ANX1HR	ANX4HR	CONDITION
8	7	7	Placebo
10	10	10	Placebo
9	7	8	Placebo
7	6	6	Placebo
7	7	7	Placebo
9	4	5	Valium®
10	6	8	Valium®
9	5	5	Valium®
8	3	5	Valium®
6	3	4	Valium®
8	5	3	Experimental Drug
6	5	2	Experimental Drug
9	8	4	Experimental Drug
10	9	4	Experimental Drug
7	6	3	Experimental Drug

Appendix C

Sample Data Files Used in Text

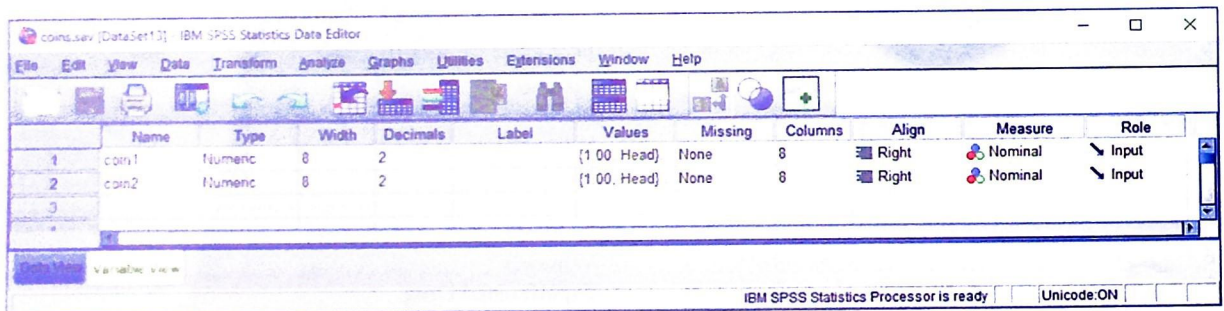
Several data files are used in examples throughout this text. This appendix contains a list of each, along with details on how the variables are defined and what is entered. Each section where a file is modified or used is identified.

Practice Datasets 1, 2, and 3 are in
Appendix B.

COINS.sav

Created in Section 8.1

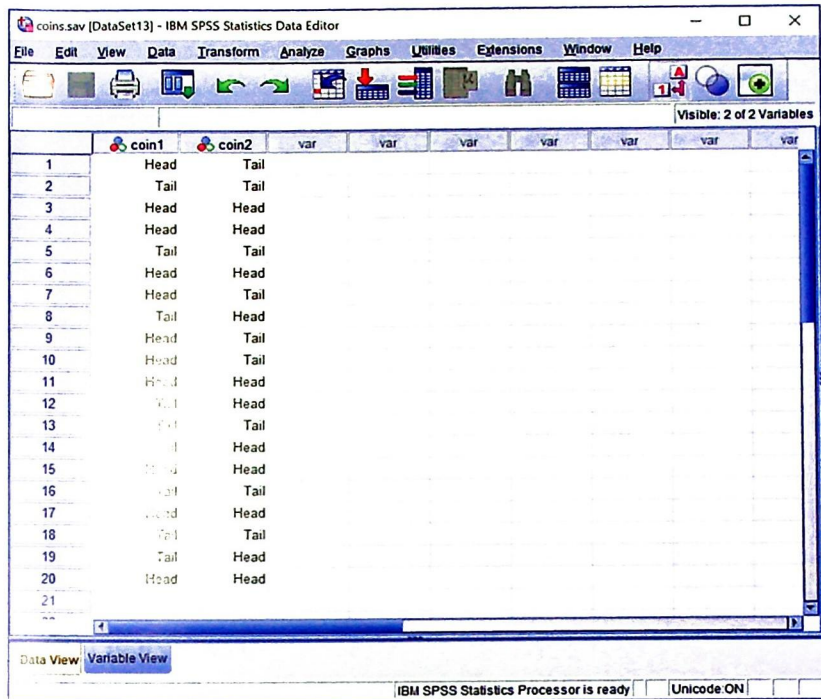
Used also in Section 8.2



	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	coin1	Numenc	8	2		(1 00 Head)	None	8	Right	Nominal	Input
2	coin2	Numenc	8	2		(1 00 Head)	None	8	Right	Nominal	Input

Variable view

IBM SPSS Statistics Processor is ready Unicode:ON

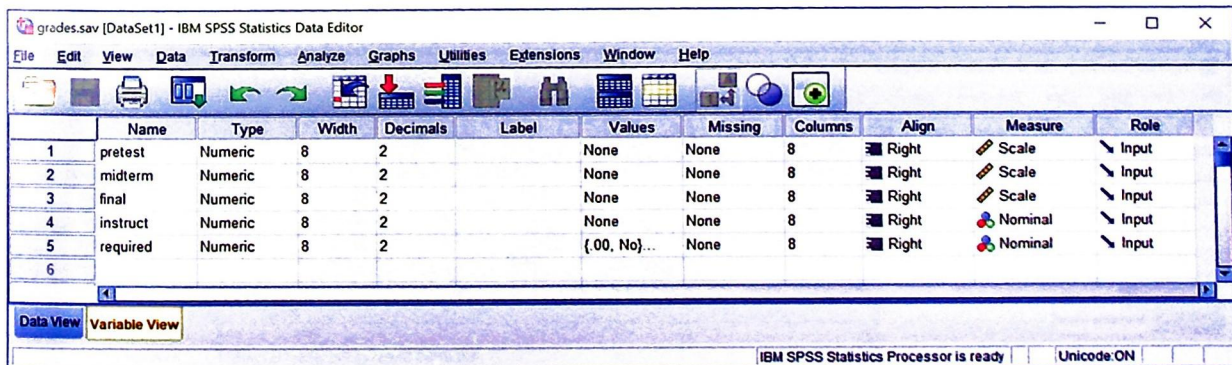


GRADES.sav

Created in Section 6.4

Used also in Sections 4.5, 7.2, 7.3, 7.4, 7.5

Used also in Appendix A Section A.1 and A.3



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

Visible: 5 of 5 Variables

	pretest	midterm	final	instruct	required
1	56.00	64.00	69.00	1.00	No
2	79.00	91.00	89.00	1.00	No
3	68.00	77.00	81.00	1.00	No
4	59.00	69.00	71.00	1.00	Yes
5	64.00	77.00	75.00	1.00	Yes
6	74.00	88.00	86.00	1.00	Yes
7	73.00	85.00	85.00	1.00	Yes
8	47.00	64.00	69.00	2.00	No
9	78.00	98.00	100.00	2.00	No
10	61.00	77.00	85.00	2.00	No
11	68.00	86.00	93.00	2.00	Yes
12	64.00	77.00	87.00	2.00	Yes
13	53.00	67.00	76.00	2.00	Yes
14	71.00	85.00	95.00	2.00	Yes
15	61.00	73.00	97.00	3.00	No
16	57.00	77.00	89.00	3.00	No
17	49.00	65.00	83.00	3.00	No
18	71.00	93.00	100.00	3.00	Yes
19	61.00	83.00	94.00	3.00	Yes
20	58.00	75.00	92.00	3.00	Yes
21	58.00	74.00	92.00	3.00	Yes
22					

IBM SPSS Statistics Processor is ready Unicode ON

HEIGHT.sav

Created in Section 4.2

Used also in Section 4.3

Used also throughout Chapter 5

Used also in Sections 6.2 and 7.6

Used also in Appendix A section A.1 and A.2

height.sav [DataSet2] - IBM SPSS Statistics Data Editor

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	HEIGHT	Numeric	8	2		None	None	8	Right	Scale	Input
2	WEIGHT	Numeric	8	2		None	None	8	Right	Scale	Input
3	SEX	Numeric	8	2		[1 00 Male]	None	8	Right	Nominal	Input
4											

IBM SPSS Statistics Processor is ready Unicode ON

height.sav [DataSet2] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

Visible: 3 of 3 Variables

	HEIGHT	WEIGHT	SEX	var	var	var	var	var	var
1	66.00	150.00	1.00						
2	69.00	155.00	1.00						
3	73.00	160.00	1.00						
4	72.00	160.00	1.00						
5	68.00	150.00	1.00						
6	63.00	140.00	1.00						
7	74.00	165.00	1.00						
8	70.00	150.00	1.00						
9	65.00	110.00	2.00						
10	64.00	100.00	2.00						
11	69.00	95.00	2.00						
12	67.00	110.00	2.00						
13	64.00	105.00	2.00						
14	63.00	100.00	2.00						
15	67.00	110.00	2.00						
16	65.00	105.00	2.00						
17									

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode ON

QUESTIONS.sav

Created in Section 2.2

questions.sav [DataSet4] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	q1	Numeric	8	2		None	None	8	Right	Scale	Input
2	q2	Numeric	8	2		None	None	8	Right	Scale	Input
3	q3	Numeric	8	2		None	None	8	Right	Scale	Input
4											

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode ON

questions.sav [DataSet4] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

Visible: 3 of 3 Variables

	q1	q2	q3	var	var	var	var	var	var
1	3.00	3.00	4.00						
2	4.00	2.00	3.00						
3	2.00	2.00	3.00						
4	1.00	3.00	1.00						
5									

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode ON

race1.sav [DataSet1] - IBM SPSS Statistics Data Editor

Visible: 4 of 4 Variables

	long	medium	short	experience
1	1.00	4.00	6.00	2.00
2	2.00	3.00	4.00	2.00
3	3.00	2.00	7.00	2.00
4	4.00	5.00	3.00	2.00
5	5.00	1.00	10.00	1.00
6	6.00	8.00	5.00	1.00
7	7.00	7.00	12.00	1.00
8	8.00	6.00	1.00	1.00
9				

Data View Variable View

IBM SPSS Statistics Processor is ready | Unicode ON

Modified in Section 8.5 to be:

race1.sav [DataSet1] - IBM SPSS Statistics Data Editor

Visible: 4 of 4 Variables

	long	medium	short	experience
1	1.00	4.00	6.00	2.00
2	2.00	3.00	4.00	2.00
3	3.00	2.00	7.00	2.00
4	4.00	5.00	3.00	2.00
5	5.00	1.00	10.00	1.00
6	6.00	8.00	5.00	1.00
7	7.00	7.00	12.00	1.00
8	8.00	6.00	1.00	1.00
9	9.00	10.00	3.00	.00
10	10.00	9.00	9.00	.00
11	11.00	11.00	11.00	.00
12	12.00	12.00	2.00	.00
13				

Data View Variable View

IBM SPSS Statistics Processor is ready | Unicode ON

Modified version also used in Section 8.6

RATER.sav

Created in Section 9.5

*Untitled2 [DataSet3] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

Visible: 2 of 2 Variables

	rater1	rater2	var	var	var	var
1	7.00	7.00				
2	8.00	8.00				
3	4.00	3.00				
4	5.00	5.00				
5	6.00	6.00				
6	4.00	5.00				
7	5.00	5.00				
8	8.00	8.00				
9	3.00	2.00				
10	1.00	1.00				
11						

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

SAMPLE.sav

Created in Section 1.4

*SAMPLE.sav [DataSet20] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	ID	Numeric	8	2		None	None	8	Right	Scale	Input
2	DAY	Numeric	8	2		{1.00, Mon/}	None	8	Right	Nominal	Input
3	TIME	Numeric	8	2	What is the tim	{1.00, Morni	None	8	Right	Nominal	Input
4	MORNING	Numeric	8	2	Are you a morn	{00, No}	None	9	Right	Nominal	Input
5	GRADE	Numeric	8	2		None	None	8	Right	Scale	Input
6	WORK	Numeric	8	2		{00, No}	None	8	Right	Nominal	Input
7											

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

SAMPLE1.sav [DataSet20] - IBM SPSS Statistics Data Editor

Visible: 6 of 6 Variables

	ID	DAY	TIME	MORNING	GRADE	WORK
1	4593.00	2.00	2.00	.00	85.00	.00
2	1901.00	1.00	1.00	1.00	83.00	1.00
3	8734.00	2.00	1.00	.00	80.00	.00
4	1909.00	1.00	1.00	1.00	73.00	1.00
5						

IBM SPSS Statistics Processor is ready Unicode ON

Used throughout Chapter 1
Modified in Section 1.7 (TRAINING added)

SAMPLE1.sav [DataSet20] - IBM SPSS Statistics Data Editor

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	ID	Numeric	8	2		None	None	8	Right	Scale	Input
2	DAY	Numeric	8	2		{1.00, Mon/...	None	8	Right	Nominal	Input
3	TIME	Numeric	8	2	What is the tim...	{1.00, Morni...	None	8	Right	Nominal	Input
4	MORNING	Numeric	8	2	Are you a morn...	{0.0, No}...	None	8	Right	Nominal	Input
5	GRADE	Numeric	8	2		None	None	8	Right	Scale	Input
6	WORK	Numeric	8	2		{0.0, No}...	None	8	Right	Nominal	Input
7	TRAINING	Numeric	8	2		{0.0, No}...	None	8	Right	Nominal	Input
8											

IBM SPSS Statistics Processor is ready Unicode ON

SAMPLE1.sav [DataSet20] - IBM SPSS Statistics Data Editor

Visible: 7 of 7 Variables

	ID	DAY	TIME	MORNING	GRADE	WORK	TRAINING
1	4593.00	2.00	2.00	.00	85.00	.00	1.00
2	1901.00	1.00	1.00	1.00	83.00	1.00	1.00
3	8734.00	2.00	1.00	.00	80.00	.00	.00
4	1909.00	1.00	1.00	1.00	73.00	1.00	.00
5							

IBM SPSS Statistics Processor is ready Unicode ON

Used also in Section 2.1 and 2.2
Used also throughout Chapter 3
Used also in Section 6.3

SAT.sav

Created in Section 7.7

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	SAT	Numeric	8	2		None	None	8	Right	Scale	Input
2	GRE	Numeric	8	2		None	None	8	Right	Scale	Input
3	GROUP	Numeric	8	2		{ 00, No Trai...	None	8	Right	Nominal	Input
4											

IBM SPSS Statistics Processor is ready | Unicode:ON

	SAT	GRE	GROUP	var	var	var	var	var	var
1	580 00	600 00	00						
2	520 00	520 00	00						
3	500 00	510 00	00						
4	410 00	400 00	00						
5	650 00	630 00	00						
6	480 00	480 00	00						
7	500 00	490 00	1 00						
8	640 00	650 00	1 00						
9	500 00	480 00	1 00						
10	600 00	510 00	1 00						
11	580 00	570 00	1 00						
12	450 00	500 00	1 00						
13	520 00	520 00	2 00						
14	620 00	630 00	2 00						
15	550 00	550 00	2 00						
16	500 00	510 00	2 00						
17	540 00	550 00	2 00						
18	600 00	600 00	2 00						
19									

IBM SPSS Statistics Processor is ready | Unicode:ON

TIME.sav

Created in Section 7.4

	before	during	after	group	var	var	var
1	3 00	5 00	4 00	1 00			
2	4 00	4 00	3 00	1 00			
3	3 00	4 00	5 00	1 00			
4	2 00	4 00	2 00	2 00			
5	4 00	3 00	4 00	2 00			
6	5 00	2 00	4 00	2 00			
7							

IBM SPSS Statistics Processor is ready | Unicode:ON

Appendix D

SPSS Syntax Basics

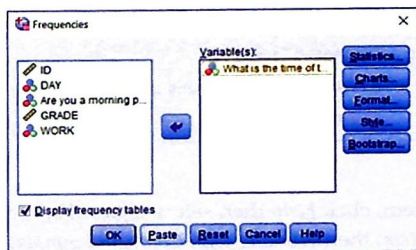
Introduction to Syntax

IBM SPSS Statistics has been easy to use with its point and click interface for several decades. Before that, however, SPSS required users to write programs to conduct their analyses. In fact, all the point and click interface does is create syntax for you that is run.

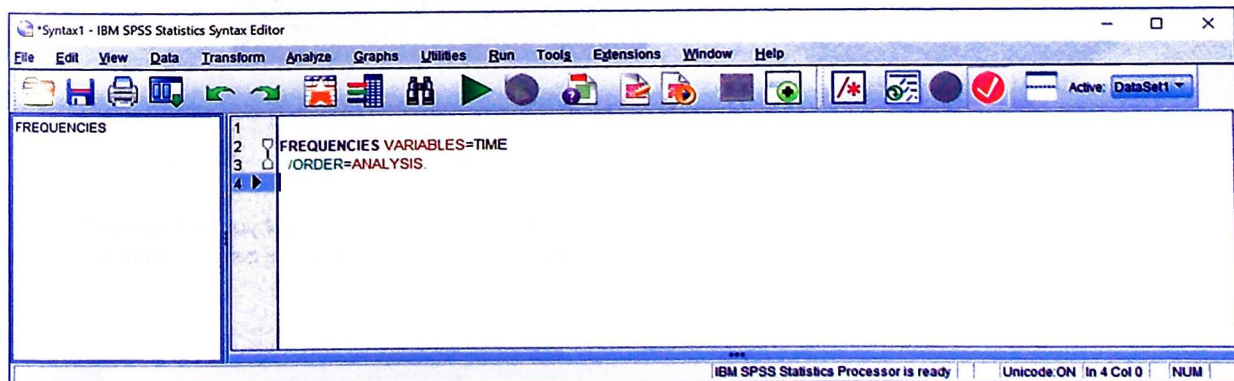
Using syntax can be very useful if you want to save an analysis and run it later. Understanding it is an important part of being able to understand your output as well.

This text will not cover how to create SPSS syntax from scratch. Rather, it will simply cover how to get SPSS to create it for you, and how to read the syntax it creates.

Having SPSS Create Syntax



Most SPSS Dialog Boxes will have a *Paste* option in them. Clicking *Paste* instead of *OK* will put the relevant SPSS Syntax in a Syntax Window.



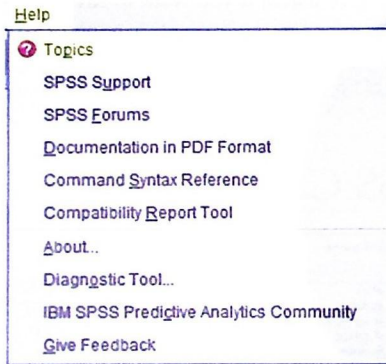
The syntax window is highlighted and color coded to help you understand what the commands are asking SPSS to do. In the example above, the command that was run was the *Frequencies* command. It was run on the variable TIME.

Many SPSS commands have options that are added to them but are not necessarily important at the level of this text. For example, the `/ORDER=ANALYSIS` option above.

SPSS Syntax Format and SPSS Help

SPSS syntax is written like sentences. In fact, each one ends with a period (“.”). The number of lines it is on does not matter—so it is often best to use several lines to make it easier to read.

Rather than provide extensive coverage in this text, I suggest that if you are interested in SPSS Syntax then you should use the excellent help system provided within SPSS itself.



To access that help system, click *Help* then select *Topics*. This will open the SPSS Help website. Select *Core System*, then *Working with Command Syntax*.



Running SPSS Syntax

Whether SPSS creates syntax for you, whether you create it yourself, or whether you modify syntax that SPSS has created, at some point you are going to want to use that syntax.



From a Syntax Window simply select *Run* and then *All*. Alternatively, you can select just some of the text in the window with your mouse and then click *Selection* instead of *All*.

Saving and Loading SPSS Syntax

Syntax files have the extension “.sps” and can be saved and loaded just like other files. To load a file select *File—Open—Syntax*.

Appendix E

Glossary

- All Inclusive** A set of events that encompasses every possible outcome. Also referred to as *exhaustive*.
- Alternative Hypothesis** The opposite of the null hypothesis, normally showing that there is a true difference. Generally, this is the statement that the researcher would like to support.
- Case Processing Summary** A section of SPSS output that lists the number of subjects used in the analysis.
- Coefficient of Determination** The value of the correlation, squared. It provides the proportion of variance accounted for by the relationship.
- Cohen's *d*** A common and simple measure of effect size that standardizes the difference between groups.
- Correlation Matrix** A section of SPSS output in which correlation coefficients are reported for all pairs of variables.
- Covariate** A variable known to be related to the dependent variable but not treated as an independent variable. Used in ANCOVA as a statistical control technique.
- Data Window** The SPSS window that contains the data in a spreadsheet format. This is the window used for running most commands.
- Dependent Variable** An outcome or response variable. The dependent variable is normally dependent on the independent variable.
- Descriptive Statistics** Statistical procedures that organize and summarize data.
- Dialog Box** A window that allows you to enter information that SPSS will use in a command.
- Dichotomous Variables** Variables with only two levels (e.g., gender).
- Discrete Variable** A variable that can have only certain values (i.e., values between which there is no score, like A, B, C, D, F).
- Effect Size** A measure that allows one to judge the relative importance of a difference or relationship by reporting the size of a difference.
- Eta Squared (η^2)** A measure of effect size used in Analysis of Variance models.
- Grouping Variable** In SPSS, the variable used to represent group membership. SPSS often refers to independent variables as grouping variables; SPSS sometimes refers to grouping variables as independent variables.
- Independent Events** Two events are independent if information about one event gives no information about the second event (e.g., two flips of a coin).
- Independent Variable** The variable whose levels (values) determine the group to which a subject belongs. A true independent variable is manipulated by the researcher. See Grouping Variable.
- Inferential Statistics** Statistical procedures designed to allow the researcher to draw inferences about a population on the basis of a sample.
- Interaction** With more than one independent variable, an interaction occurs when a level of one independent variable affects the influence of another independent variable.
- Internal Consistency** A reliability measure that assesses the extent to which all of the items in an instrument measure the same construct.
- Interval Scale** A measurement scale where items are placed in mutually exclusive categories, with equal intervals between values. Appropriate transformations include counting, sorting, and addition/subtraction.
- Levels** The values that a variable can have. A variable with three levels has three possible values.
- Mean** A measure of central tendency where the sum of the deviation scores equals zero.
- Median** A measure of central tendency representing the middle of a distribution when the data are sorted from low to high. Fifty percent of the cases are below the median.
- Mode** A measure of central tendency representing the value (or values) with the most subjects (the score with the greatest frequency).
- Mutually Exclusive** Two events are mutually exclusive when they cannot occur simultaneously.
- Nominal Scale** A measurement scale where items are placed in mutually exclusive categories. Differentiation

is by name only (e.g., race, sex). Appropriate categories include "same" or "different." Appropriate transformations include counting.

Normal Distribution A symmetric, unimodal, bell-shaped curve.

Null Hypothesis The hypothesis to be tested, normally in which there is no true difference. It is mutually exclusive of the alternative hypothesis.

Ordinal Scale A measurement scale where items are placed in mutually exclusive categories, in order. Appropriate categories include "same," "less," and "more." Appropriate transformations include counting and sorting.

Outliers Extreme scores in a distribution. Scores that are very distant from the mean and the rest of the scores in the distribution.

Output Window The SPSS window that contains the results of an analysis. The left side summarizes the results in an outline. The right side contains the actual results.

Percentiles (Percentile Ranks) A relative score that gives the percentage of subjects who scored at the same value or lower.

Pooled Standard Deviation A single value that represents the standard deviation of two groups of scores.

Protected Dependent *t* Tests *T* tests where the acceptable Type I error rate has been adjusted to prevent the inflation of a Type I error.

Quartiles The points that define a distribution into four equal parts: the scores at the 25th, 50th, and 75th percentile ranks.

Random Assignment A procedure for assigning subjects to conditions in which each subject has an equal chance of being assigned to any condition.

Range A measure of dispersion representing the number of points from the highest score through the lowest score.

Ratio Scale A measurement scale where items are placed in mutually exclusive categories, with equal intervals between values and a true zero. Appropriate transformations include counting, sorting, addition/subtraction, and multiplication/division.

Reliability An indication of the consistency of a scale. A reliable scale is internally consistent and stable over time.

Robust A test is said to be robust if it continues to provide accurate results even after the violation of some assumptions.

Significance A difference is said to be significant if the probability of making a Type I error is less than the accepted limit (normally 5%). If a difference is significant, the null hypothesis is rejected.

Skew The extent to which a distribution is not symmetrical. A positive skew has outliers on the positive (right) side of the distribution. A negative skew has outliers on the negative (left) side of the distribution.

Source Table The results of ANOVA are normally presented in the form of a source table in which rows represent a source of variability and the columns represent different amounts of the variability that can be attributed to that source.

Standard Deviation A measure of dispersion representing a special type of average deviation from the mean.

Standard Error of Estimate The equivalent of the standard deviation for a regression line. The data points will be normally distributed around the regression line with a standard deviation equal to the standard error of the estimate.

Standard Normal Distribution A normal distribution with a mean of 0.0 and a standard deviation of 1.0.

Temporal Stability This is achieved when reliability measures have determined that scores remain stable over multiple administrations of the instrument.

Tukey's *HSD* A post-hoc comparison purported to reveal an "honestly significant difference" (*HSD*).

Type I Error A Type I error occurs when the researcher erroneously rejects the null hypothesis.

Type II Error A Type II error occurs when the researcher erroneously fails to reject the null hypothesis.

Valid Data Data that SPSS will use in its analyses.

Validity An indication of the accuracy of a scale.

Variance A measure of dispersion equal to the squared standard deviation.

Appendix F

Selecting the Appropriate Inferential Test

Being able to select the appropriate inferential test for SPSS to run is one of the most important skills you can learn. Unfortunately, the way most statistics classes and statistics texts are set up, each statistical procedure is presented in isolation, and there is rarely an opportunity to synthesize the information and understand when each test is appropriate.

This text contains a decision tree on the last page. However, novices sometimes have trouble using that tree because they do not understand the terms used. This appendix expands on the decision tree and provides a comprehensive way to determine which test to run.

To help you use this section of the text, there will be a reference to a “branch” of the decision tree.

Branch 1

The first step in determining what type of statistical test to run is deciding what your main question is.

Sometimes you want to know if a group is “significantly different” from another. This can involve means or shapes of distributions. The basic question, however, is the same. You want to know if the things you are comparing are the same as each other or different from each other. For example, you want to know if a group that received a new treatment had a significantly shorter hospital stay than a group that did not receive the new treatment. If this is what you are trying to do, go to Branch 2.

Other times you are more interested in knowing whether or not there is a relationship between two variables, and if so, how strong that relationship is. These are known as correlations. Here, rather than looking for differences, you are simply looking for stable relationships. For example, is height related to weight? Do students who miss class more often do worse academically? Often, the variables here are continuous and have many levels rather than just a few. If this is what you are interested in, go to Branch 3.

More powerful than association is prediction. If you would like to be able to predict or guess the value of a variable from some other information that you have, then you are interested in regression. For example, if an insurance company wants to predict how much you will cost them in claims based on your driving history, that is a problem for regression. If these are the types of questions you are interested in, go to Branch 6.

Branch 2

Your Decisions So Far:

- Looking for Differences in Groups

The next step is to determine how many Dependent Variables you have. Dependent Variables are the variables that are different from each other. Most of the time you will have only a single Dependent Variable (although you could have one or more Independent Variables).

If you get Independent and Dependent Variables confused, a good way to help clarify is to rephrase the problem as “I am looking for the effect of the (Independent Variable) on the (Dependent Variable).”

- If you have one Dependent Variable, see Branch 9.
- If you have more than one Dependent Variable, see Branch 10.

Branch 3

Your Decisions So Far:

- Measuring Strength of Association

In general, correlations measure the strength of a relationship or association.

This text covers what are known as bivariate correlations—that is, correlations between only two variables at a time. In addition, this text covers only linear correlations—or correlations that assume the relationship being measured generally looks like a line.

In deciding which correlation is appropriate, first you must determine if you can do a parametric or nonparametric correlation. Parametric Tests generally require that the Dependent Variables are measured on an Interval or Ratio measurement scale and that the variables are approximately normally distributed. Nonparametric Tests do not make that assumption.

If either of the variables in your relationship is ordinal (e.g., ranks) you must do a nonparametric correlation. If one of your variables is nominal, you are just out of luck with correlations.

- If you can do a Parametric Correlation, see Branch 4.
- If you must do a Nonparametric Correlation, see Branch 5.

Branch 4

Your Decisions So Far:

- Measuring Strength of Association
- You can do a Parametric Correlation

The appropriate test to do is a Pearson r . This test is covered in detail in Section 5.1 of this text. It is accessed in SPSS at Analyze → Correlate → Bivariate.

Answers range from -1 to $+1$. Values close to 0 mean there is a weak relationship. Values closer to $+1$ or -1 mean a stronger relationship. Positive values mean as one variable gets larger, the other variable also gets larger. Negative values mean as one variable gets larger, the other variable gets smaller.

Branch 5

Your Decisions So Far:

- Measuring Strength of Association
- You must do a Nonparametric Correlation

The appropriate test to do is a Spearman ρ . This test is covered in detail in Section 5.2 of this text. It is accessed in SPSS at Analyze → Correlate → Bivariate and then selecting Spearman in the dialog box that comes up.

Answers range from -1 to $+1$. Values close to 0 mean there is a weak relationship. Values closer to $+1$ or -1 mean a stronger relationship. Positive values mean as one variable gets larger, the other variable also gets larger. Negative values mean as one variable gets larger, the other variable gets smaller.

Branch 6

Your Decisions So Far:

- Making Predictions

Predictions are a powerful use of statistics. In this text, we only cover prediction models that assume the variables are related to each other in linear ways. If you have nonlinear relationships, they are beyond the scope of this text.

This text uses the term “Independent Variable” when, in fact, sometimes prediction is done when there is not a true Independent Variable. If you have a design where there is not a true Independent Variable, the variables you use to make a prediction should be considered Independent Variables for purposes of this decision process.

- If you have a single Independent Variable, see Branch 7.
- If you have multiple Independent Variables that you want to use to predict the value of a single Dependent Variable (e.g., predict a GPA from ACT scores, classes missed, and hours spent studying), see Branch 8.

Branch 7

Your Decisions So Far:

- Making Predictions
- Single Independent Variable

The appropriate test to do is a Simple Linear Regression. This test is covered in detail in Section 5.3 of this text. It is accessed in SPSS at Analyze → Regression → Linear.

The output will have a B column that provides the answers. The B for Constant is your Y-Intercept, and the B next to the name of your Independent Variable is the slope of the line.

Branch 8

Your Decisions So Far:

- Making Predictions
- Multiple Independent Variables

The appropriate test to do is a Multiple Linear Regression. This test is covered in detail in Section 5.4 of this text. It is accessed in SPSS at Analyze → Regression → Linear and entering more than one Independent Variable.

The output will have a B column that provides the answers. The B for Constant is your Y-Intercept, and the Bs next to the names of your Independent Variables are the weights for each of them.

Branch 9

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable

The next question to ask is whether you can do a Parametric Test or whether you have to do a Nonparametric Test. Parametric Tests generally require that the Dependent Variables are measured on an Interval or Ratio measurement scale, and the variables are approximately normally distributed. With Nonparametric Tests, you do not make that assumption.

- If you can do a Parametric Test, see Branch 11.
- If you must do a Nonparametric Test, see Branch 26.

Branch 10

Your Decisions So Far:

- Looking for Differences in Groups
- More than One Dependent Variable

The appropriate test to do is a MANOVA (Multivariate Analysis of Variance). This test is covered in detail in Section 7.7 of this text. It is accessed in SPSS at Analyze → General Linear Model → Multivariate.

This text does not cover tests for Nonparametric equivalents of MANOVA. Also, please note that the Advanced Module of IBM SPSS Statistics is required to run this command.

Branch 11

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test

Sometimes when a researcher cannot implement appropriate procedural controls (e.g., random assignment of participants to groups), the overall analysis can be improved by “covarying out” variables that the researcher knows may have an effect on the Dependent Variable.

For example, a researcher may be comparing two different sections of a class, but was unable to assign students to the sections (the students self-selected). The researcher knows that overall GPA is likely to have an effect on the grade in the course. The researcher can, therefore, “covary out” the effect of cumulative GPA from the grades in the two sections to make a better comparison as to whether or not the two sections were different in some other way (e.g., because of a new teaching method).

- If you would like to analyze your data with a Covariate, see Branch 12.
- If you are not going to use a Covariate, see Branch 13.

The appropriate test to do is a Spearman *r*_{ho}. This test is covered in detail in Section 5.2 of this text. It is accessed in SPSS at Analyze → Correlate → Bivariate and then selecting Spearman in the dialog box that comes up.

Answers range from -1 to +1. Values close to 0 mean there is a weak relationship. Values closer to +1 or -1 mean a stronger relationship. Positive values mean as one variable gets larger, the other variable also gets larger. Negative values mean as one variable gets larger, the other variable gets smaller.

Branch 6

Your Decisions So Far:

- Making Predictions

Predictions are a powerful use of statistics. In this text, we only cover prediction models that assume the variables are related to each other in linear ways. If you have nonlinear relationships, they are beyond the scope of this text.

This text uses the term “Independent Variable” when, in fact, sometimes prediction is done when there is not a true Independent Variable. If you have a design where there is not a true Independent Variable, the variables you use to make a prediction should be considered Independent Variables for purposes of this decision process.

- If you have a single Independent Variable, see Branch 7.
- If you have multiple Independent Variables that you want to use to predict the value of a single Dependent Variable (e.g., predict a GPA from ACT scores, classes missed, and hours spent studying), see Branch 8.

Branch 7

Your Decisions So Far:

- Making Predictions
- Single Independent Variable

The appropriate test to do is a Simple Linear Regression. This test is covered in detail in Section 5.3 of this text. It is accessed in SPSS at Analyze → Regression → Linear.

The output will have a B column that provides the answers. The B for Constant is your Y-Intercept, and the B next to the name of your Independent Variable is the slope of the line.

Branch 8

Your Decisions So Far:

- Making Predictions
- Multiple Independent Variables

The appropriate test to do is a Multiple Linear Regression. This test is covered in detail in Section 5.4 of this text. It is accessed in SPSS at Analyze → Regression → Linear and entering more than one Independent Variable.

The output will have a B column that provides the answers. The B for Constant is your Y-Intercept, and the Bs next to the names of your Independent Variables are the weights for each of them.

Branch 9

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable

The next question to ask is whether you can do a Parametric Test or whether you have to do a Nonparametric Test. Parametric Tests generally require that the Dependent Variables are measured on an Interval or Ratio measurement scale, and the variables are approximately normally distributed. With Nonparametric Tests, you do not make that assumption.

- If you can do a Parametric Test, see Branch 11.
- If you must do a Nonparametric Test, see Branch 26.

Branch 10

Your Decisions So Far:

- Looking for Differences in Groups
- More than One Dependent Variable

The appropriate test to do is a MANOVA (Multivariate Analysis of Variance). This test is covered in detail in Section 7.7 of this text. It is accessed in SPSS at Analyze → General Linear Model → Multivariate.

This text does not cover tests for Nonparametric equivalents of MANOVA. Also, please note that the Advanced Module of IBM SPSS Statistics is required to run this command.

Branch 11

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test

Sometimes when a researcher cannot implement appropriate procedural controls (e.g., random assignment of participants to groups), the overall analysis can be improved by “covarying out” variables that the researcher knows may have an effect on the Dependent Variable.

For example, a researcher may be comparing two different sections of a class, but was unable to assign students to the sections (the students self-selected). The researcher knows that overall GPA is likely to have an effect on the grade in the course. The researcher can, therefore, “covary out” the effect of cumulative GPA from the grades in the two sections to make a better comparison as to whether or not the two sections were different in some other way (e.g., because of a new teaching method).

- If you would like to analyze your data with a Covariate, see Branch 12.
- If you are not going to use a Covariate, see Branch 13.

Branch 12

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- Covariate

The appropriate test to do is ANCOVA (Analysis of Covariance). This test is covered in detail in Section 7.6 of this text. It is accessed in SPSS at Analyze → General Linear Model → Univariate and by entering a variable in the Covariate space.

Branch 13

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate

Next, it is time to make a decision about your Independent Variables. The easiest analyses have a single Independent Variable (e.g., treatment); however, more complex analyses can have multiple Independent Variables that are examined at the same time (e.g., treatment and time).

- If you are simply comparing a single sample to a known population, see Branch 14.
- If you have a single Independent Variable, see Branch 15.
- If you have multiple Independent Variables, see Branch 22.

Branch 14

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Comparison of a Sample to a Population

The appropriate test to do is a single-sample t Test. This test is covered in detail in Section 6.2 of this text. It is accessed in SPSS at Analyze → Compare Means → One-Sample T Test.

Branch 15

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test

- No Covariate
- Single Independent Variable

The number of levels of your Independent Variable also impacts which test is appropriate. Students often get levels of a variable confused with the variable itself. Levels of a variable refer to the distinct and discrete values that it can take on. For example, the variable “sex” has two levels (male and female). If you were comparing three different instructors, the variable “instructor” would have three levels.

- If you have two levels of your Independent Variable, see Branch 16.
- If you have more than two levels of your Independent Variable, see Branch 17.

Branch 16

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Single Independent Variable
- Two Levels of the Independent Variable

Next, you need to determine what kind of design produced the two levels of your Independent Variable.

A Repeated-Measures Design is where the data in the various conditions are in some way related to each other. For example, a pre-test/post-test design or a design utilizing twins would fall into this category. These designs are sometimes called Correlated Groups Designs or Paired Samples Designs.

In an Independent Groups Design, the data in each group are independent of each other. This is the classic Experimental Group/Control Group Design where each participant is in one (and only one) group.

- If you have an Independent Groups Design, see Branch 20.
- If you have a Repeated-Measures Design, see Branch 21.

Branch 17

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Single Independent Variable
- More Than Two Levels of the Independent Variable

Next, you need to determine what kind of design produced the levels of your Independent Variable.

A Repeated-Measures Design is where the data in the various conditions are in some way related to each other. For example, comparing grades of the same students when they were freshmen, sophomores, juniors, and then seniors would fall into this category. These designs are sometimes called Correlated Groups Designs, Within-Subjects Designs, or Paired Samples Designs.

In an Independent Groups Design, the data in each group are independent of each other. This is the classic Experimental Group/Control Group Design where each participant is in one (and only one) group. For example, if you were comparing four different PSY101 instructors, you would use an Independent Groups Design. Sometimes this is called a Between-Subjects Design.

- If your Independent Variable represents Independent Groups, see Branch 18.
- If your Independent Variable represents Repeated Measures, see Branch 19.

Branch 18

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Single Independent Variable
- More Than Two Levels of the Independent Variable
- Independent Groups

The appropriate test to do is a one-way ANOVA (technically a one-way between-subjects ANOVA). This test is covered in detail in Section 7.2 of this text. It is accessed in SPSS at Analyze → Compare Means → One-Way ANOVA.

Branch 19

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Single Independent Variable
- More Than Two Levels of the Independent Variable
- Repeated Measures

The appropriate test to do is a repeated-measures ANOVA. This test is covered in detail in Section 7.4 of this text. It is accessed in SPSS at Analyze → General Linear Model → Repeated Measures.

Note: This procedure requires the Advanced Module in SPSS.

Branch 20

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Single Independent Variable
- Two Levels of the Independent Variable
- Independent Groups

The appropriate test to do is an independent-samples t test. This test is covered in detail in Section 6.3 of this text. It is accessed in SPSS at Analyze → Compare Means → Independent-Samples t Test.

Branch 21

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Single Independent Variable
- Two Levels of the Independent Variable
- Repeated Measures

The appropriate test to do is a paired-samples t test (sometimes called a Dependent t Test). This test is covered in detail in Section 6.4 of this text. It is accessed in SPSS at Analyze → Compare Means → Paired-Samples T Test.

Branch 22

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Multiple Independent Variables

Next, you need to determine what kind of design produced the levels of your Independent Variables.

A Repeated-Measures Design (also called Within-Subjects) is where the data in the various conditions are in some way related to each other. For example, comparing grades of the same students when they were freshmen, sophomores, juniors, and then seniors would fall into this category. These designs are sometimes called Correlated Groups Designs or Paired Samples Designs.

In an Independent Groups Design (also called Between-Subjects), the data in each group are independent of each other. This is the classic Experimental Group/Control Group Design where each participant is in one (and only one) group. For example, if you were comparing four different PSY101 instructors, you would use an Independent Groups Design.

Because you have more than one Independent Variable, your Independent Variables can all be Repeated Measures, all Independent Groups, or a mix of the two.

- If all of your Independent Variables represent Independent Groups, see Branch 23.
- If all of your Independent Variables represent Repeated Measures, see Branch 24.
- If your Independent Variables are a mix of Independent Groups and Repeated Measures, see Branch 25.

Branch 23

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Multiple Independent Variables
- Independent Measures

The appropriate test to do is a Factorial ANOVA. This test is covered in detail in Section 7.3 of this text. It is accessed in SPSS at Analyze → General Linear Model → Univariate.

Branch 24

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Multiple Independent Variables
- Repeated Measures

The appropriate test to do is a repeated-measures ANOVA. This test is covered in detail in Section 7.4 of this text. It is accessed in SPSS at Analyze → General Linear Model → Repeated Measures.

Note: This test requires the Advanced Module to be installed.

Branch 25

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Parametric Test
- No Covariate
- Multiple Independent Variables
- Both Independent and Repeated Measures

The appropriate test to do is a mixed-design ANOVA. This test is covered in detail in Section 7.4 of this text. It is accessed in SPSS at Analyze → General Linear Model → Repeated Measures.

Note: This test requires the Advanced Module to be installed.

Branch 26

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test

While Parametric Tests look for differences in Means, the data on which Nonparametric Tests are calculated often do not lend themselves to the calculation of a Mean (e.g., they are nominal or ordinal).

Thus, the first question in a Nonparametric Test is whether you are interested in differences in proportions of values (used with nominal data) or differences in the ranks of values (ordinal data).

- If you are looking for differences in proportions, see Branch 27.
- If you are looking for differences in ranks, see Branch 30.

Branch 27

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Proportions

Like their Parametric Equivalents, the number of Independent Variables you are examining for Nonparametric Tests must also be determined.

- If you have a single Independent Variable, see Branch 28.
- If you have multiple Independent Variables, see Branch 29.

Branch 28

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Proportions
- One Independent Variable

The appropriate test to do is a Chi-Square Goodness of Fit. This test is covered in detail in Section 8.1 of this text. It is accessed in SPSS at Analyze → Nonparametric Tests → One Sample.

Branch 29

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Proportions
- Multiple Independent Variables

The appropriate test to do is a Chi-Square Test of Independence. This test is covered in detail in Section 8.2 of this text. It is accessed in SPSS at Analyze → Descriptive Statistics → Crosstabs and then checking Chi-Square in the Statistics option.

Branch 30

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Ranks
- If you have more than one Independent Variable, this text does not cover the appropriate Nonparametric Test.
- If you have a single Independent Variable, however, the number of levels of that variable determines the appropriate test.
- If your Independent Variable has two levels, see Branch 31.
- If your Independent Variable has more than two levels, see Branch 32.

Branch 31

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Ranks
- Two Levels of the Independent Variable

Next, you need to determine what kind of design produced the levels of your Independent Variables.

A Repeated-Measures Design (also called Within-Subjects) is where the data in the various conditions are in some way related to each other. For example, comparing class rank of the same students when they were in high school to college would fall into this category. These designs are sometimes called Correlated Groups Designs or Paired Samples Designs.

In an Independent Groups Design (also called Between-Subjects), the data in each group are independent of each other. This is the classic Experimental Group/Control Group Design where each participant is in one (and only one) group. For example, if you were comparing two different people and their performances in various marathons, this would be an Independent Groups Design.

- If you have Independent Groups, see Branch 33.
- If you have Repeated Measures, see Branch 34.

Branch 32

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Ranks
- More Than Two Levels of the Independent Variable

Next, you need to determine what kind of design produced the levels of your Independent Variables.

A Repeated-Measures Design (also called Within-Subjects) is where the data in the various conditions are in some way related to each other. For example, comparing class rank of the same students when they were freshmen, sophomores, juniors, and then seniors would fall into this category. These designs are sometimes called Correlated Groups Designs or Paired Samples Designs.

In an Independent Groups Design (also called Between-Subjects), the data in each group are independent of each other. This is the classic Experimental Group/Control Group Design where each participant is in one (and only one) group. For example, if you were comparing three different people and their performances in various marathons, this would be an Independent Groups Design.

- If you have Independent Groups, see Branch 35.
- If you have Repeated-Measures Design, see Branch 36.

Branch 33

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Ranks
- Two Levels of the Independent Variable
- Independent Groups

The appropriate test to do is a Mann-Whitney U . This test is covered in detail in Section 8.3 of this text. It is accessed in SPSS at Analyze → Nonparametric Tests → Independent Samples.

Branch 34

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Ranks
- Two Levels of the Independent Variable
- Correlated Groups

The appropriate test to do is a Wilcoxon. This test is covered in detail in Section 8.4 of this text. It is accessed in SPSS at Analyze → Nonparametric Tests → Related Samples.

Branch 35

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Ranks
- Two Levels of the Independent Variable
- Independent Groups

The appropriate test to do is a Kruskal-Wallis H Test. This test is covered in detail in Section 8.5 of this text. It is accessed in SPSS at Analyze → Nonparametric Tests → Independent Samples.

Branch 36

Your Decisions So Far:

- Looking for Differences in Groups
- One Dependent Variable
- Nonparametric Test
- Difference in Ranks
- Two Levels of the Independent Variable
- Correlated Groups

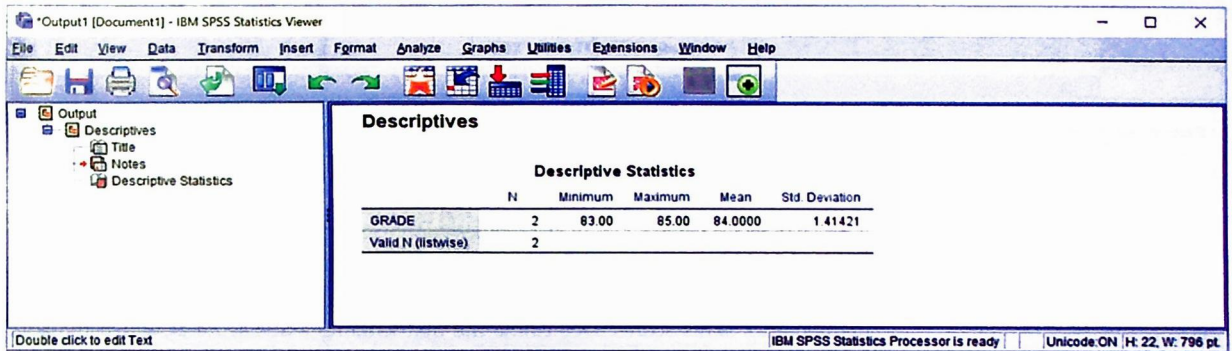
The appropriate test to do is a Friedman. This test is covered in detail in Section 8.6 of this text. It is accessed in SPSS at Analyze → Nonparametric Tests → Related Samples.

Appendix G

Answer Key

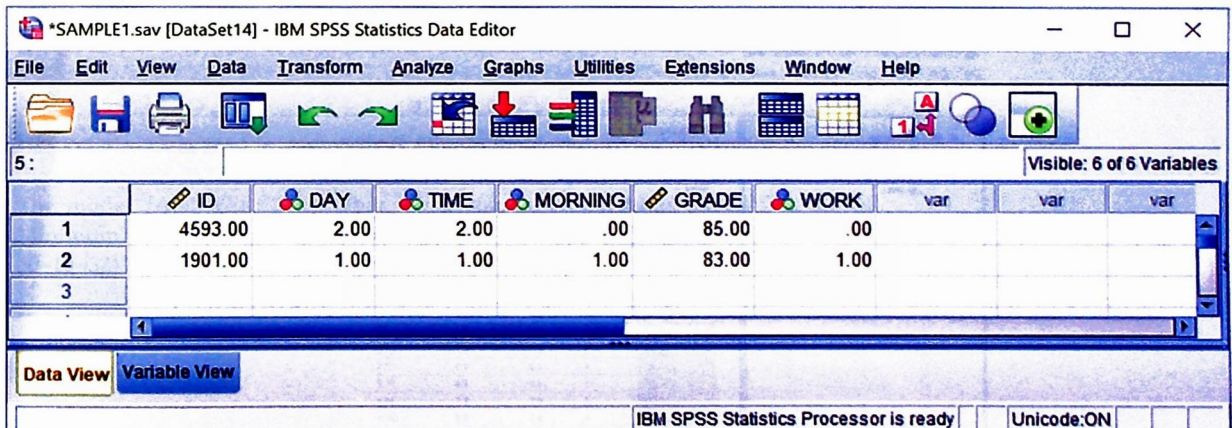
Section 1.6

Load the sample data file you created earlier (SAMPLE.sav). Run the *Descriptives* command for the variable GRADE, and view the output. Next, select the **data window** and print it.



The screenshot shows the IBM SPSS Statistics Viewer window. The main area displays the 'Descriptives' output for the variable GRADE. The output is presented as a table with the following data:

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
GRADE	2	83.00	85.00	84.0000	1.41421
Valid N (listwise)	2				



The screenshot shows the IBM SPSS Statistics Data Editor window. The data is displayed in a table with the following columns: ID, DAY, TIME, MORNING, GRADE, and WORK. The data is as follows:

	ID	DAY	TIME	MORNING	GRADE	WORK	var	var	var
1	4593.00	2.00	2.00	.00	85.00	.00			
2	1901.00	1.00	1.00	1.00	83.00	1.00			
3									

Section 1.7

Follow the previous example (where TRAINING is the new variable). Make the modifications to your SAMPLE.sav data file and save it.

*SAMPLE.sav [DataSet11] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

5 : TRAINING Visible: 7 of 7 Variables

	ID	DAY	TIME	MORNING	GRADE	WORK	TRAINING	var	v
1	4593.00	2.00	2.00	.00	85.00	.00	1.00		
2	1901.00	1.00	1.00	1.00	83.00	1.00	1.00		
3	8734.00	2.00	1.00	.00	80.00	.00	.00		
4	1909.00	1.00	1.00	1.00	73.00	1.00	.00		
5									
6									
7									

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

Section 3.1

Use Practice Data Set 1 in Appendix B. Create a frequency distribution table for the mathematics skills scores. Determine the mathematics skills score at which the 60th percentile lies.

ANSWER: 38

*Output1 (Document1) - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Frequencies
- Title
- Notes
- Statistics
- SKILL

Frequencies

Statistics

SKILL

SKILL	Valid	Percent	Valid Percent	Cumulative Percent
19.00	1	4.3	4.3	4.3
20.00	2	8.7	8.7	13.0
24.00	1	4.3	4.3	17.4
26.00	1	4.3	4.3	21.7
28.00	2	8.7	8.7	30.4
30.00	1	4.3	4.3	34.8
32.00	1	4.3	4.3	39.1
34.00	1	4.3	4.3	43.5
37.00	1	4.3	4.3	47.8
38.00	4	17.4	17.4	65.2
40.00	2	8.7	8.7	73.9
42.00	1	4.3	4.3	78.3
44.00	1	4.3	4.3	82.6
45.00	2	8.7	8.7	91.3
47.00	1	4.3	4.3	95.7
59.00	1	4.3	4.3	100.0
Total	23	100.0	100.0	

IBM SPSS Statistics Processor is ready Unicode:ON H:264.W:781 et...

Section 3.2

Use Practice Data Set 1 in Appendix B. Create a contingency table using the *Crosstabs* command. Determine the number of participants in each combination of the variables SEX and MARITAL. What percentage of participants are married? (ANSWER: 30.4%) What percentage of participants are male and married? (ANSWER: 21.7%)

Crosstabs

Case Processing Summary

	Valid		Cases Missing		Total	
	N	Percent	N	Percent	N	Percent
SEX * MARITAL	23	100.0%	0	0.0%	23	100.0%

SEX * MARITAL Crosstabulation

		MARITAL			Total	
		Single	Married	Divorced		
SEX	Male	Count	6	5	1	12
		Expected Count	6.3	3.7	2.1	12.0
	% within SEX	50.0%	41.7%	8.3%	100.0%	
	% within MARITAL	50.0%	71.4%	25.0%	52.2%	
Female	Count	6	2	3	11	
		Expected Count	5.7	3.3	1.9	11.0
	% within SEX	54.5%	18.2%	27.3%	100.0%	
	% within MARITAL	50.0%	28.6%	75.0%	47.8%	
Total	Count	12	7	4	23	
		Expected Count	12.0	7.0	4.0	23.0
	% within SEX	52.2%	30.4%	17.4%	100.0%	
	% within MARITAL	100.0%	100.0%	100.0%	100.0%	

Double click to edit Log | IBM SPSS Statistics Processor is ready | Unicode:ON H: 104, W: 833 pt

Section 3.3

Use Practice Data Set 1 in Appendix B. Obtain the descriptive statistics for the age of the participants. What is the **mean**? (ANSWER: 29.5652) The **median**? (ANSWER: 28.0) The **mode**? (ANSWER: 23.0) What is the **standard deviation**? (ANSWER: 8.9434) Minimum? (ANSWER: 18.0) Maximum? (ANSWER: 50.0) The **range**? (ANSWER: 50-18=32)

The screenshot shows the IBM SPSS Statistics Viewer interface. The left pane displays the 'Output' tree with 'Descriptives' and 'Frequencies' selected. The main window displays the following output:

Descriptives

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation
AGE	23	32.00	18.00	50.00	29.5652	8.94339
Valid N (listwise)	23					

Frequencies

Statistics

AGE	Valid	Missing
N	23	0
Median	28.0000	
Mode	23.00 ^a	
Minimum	18.00	
Maximum	50.00	

^a Multiple modes exist. The smallest value is shown.

By using the *Descriptives* command, you can get everything except the median and mode. Using the *Frequencies* command, you can get all of the information.

Section 3.4

Use Practice Data Set 1 in Appendix B. Compute the mean and standard deviation of ages for each value of marital status. What is the average age of the married participants? (ANSWER: 35.1429) The single participants? (ANSWER: 22.4167) The divorced participants? (ANSWER: 41.25)

The screenshot shows the IBM SPSS Statistics Viewer interface. The left pane displays the 'Output' tree with 'Means' selected. The main window displays the following output:

Means

Case Processing Summary

	Included		Cases Excluded		Total	
	N	Percent	N	Percent	N	Percent
AGE * MARITAL	23	100.0%	0	0.0%	23	100.0%

Report

AGE	Mean	N	Std. Deviation
MARITAL			
Single	22.4167	12	3.02890
Married	35.1429	7	5.20988
Divorced	41.2500	4	6.29153
Total	29.5652	23	8.94339

Section 3.5

Use Practice Data Set 2 in Appendix B. Determine the z-score that corresponds to each employee's salary. Determine the **mean** z-scores for salaries of male employees (ANSWER: .130) and female employees (ANSWER: -.130). Determine the **mean** z-score for salaries of the total sample. (ANSWER: 0)

*dataset2.sav [DataSet17] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

13 : ZSALARY Visible: 6 of 6 Variables

	SALARY	YOS	SEX	CLASSIFY	EDUC	ZSALARY	var	var	v
1	35000.00	8.00	1.00	2.00	14.00	.02007			
2	18000.00	4.00	2.00	1.00	10.00	-1.00344			
3	20000.00	1.00	1.00	3.00	16.00	-.88302			
4	50000.00	20.00	2.00	3.00	16.00	.92316			
5	38000.00	6.00	1.00	3.00	20.00	.20069			
6	20000.00	6.00	2.00	1.00	12.00	-.88302			
7	75000.00	17.00	1.00	3.00	20.00	2.42831			
8	40000.00	4.00	2.00	2.00	12.00	.32110			
9	30000.00	8.00	1.00	2.00	14.00	-.28096			
10	22000.00	15.00	2.00	1.00	12.00	-.76261			
11	23000.00	16.00	1.00	1.00	12.00	-.70241			
12	45000.00	2.00	2.00	3.00	16.00	.62213			
13									

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON

*Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Means
 - Title
 - Notes
 - Case Processing Summary
 - Report

Case Processing Summary

	Included		Cases Excluded		Total	
	N	Percent	N	Percent	N	Percent
Zscore(SALARY) * SEX	12	100.0%	0	0.0%	12	100.0%

Report

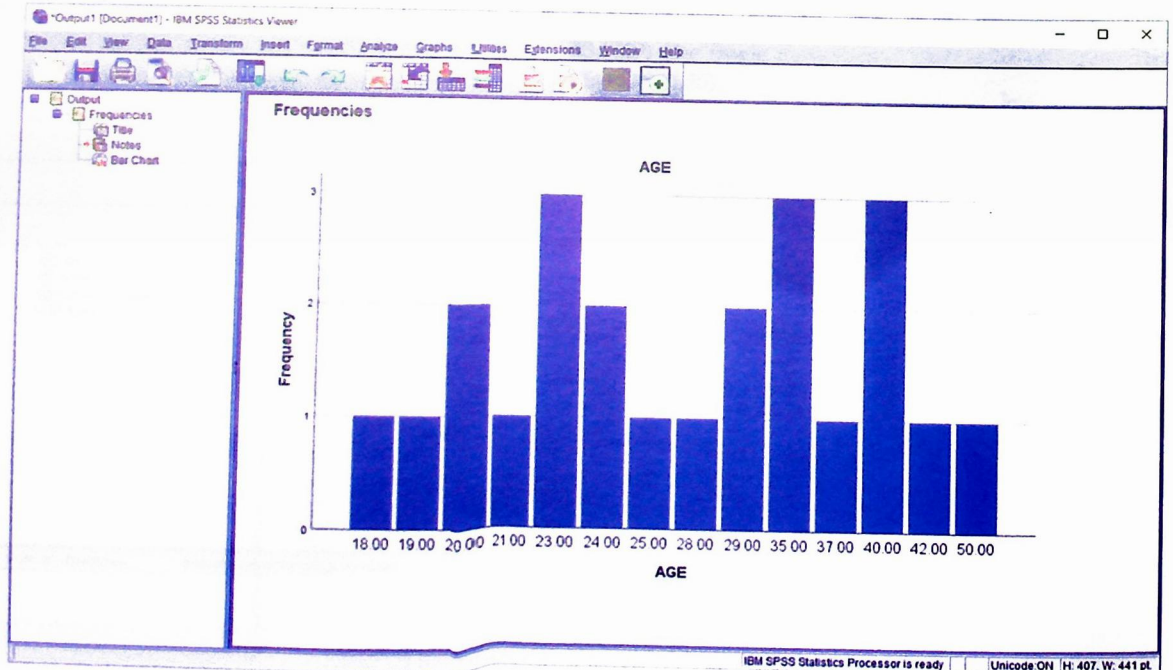
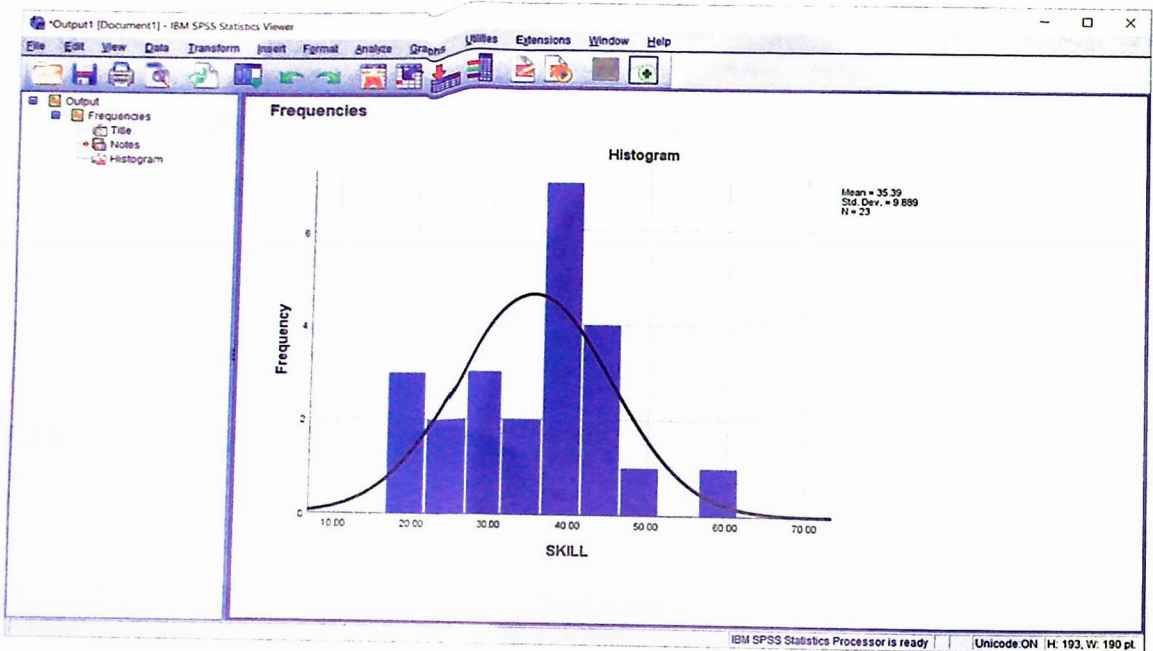
Zscore(SALARY)

SEX	Mean	N	Std. Deviation
Male	.1304467	6	1.19894414
Female	-.1304467	6	.84952581
Total	.0000000	12	1.00000000

IBM SPSS Statistics Processor is ready Unicode:ON H: 44, W: 819 pt

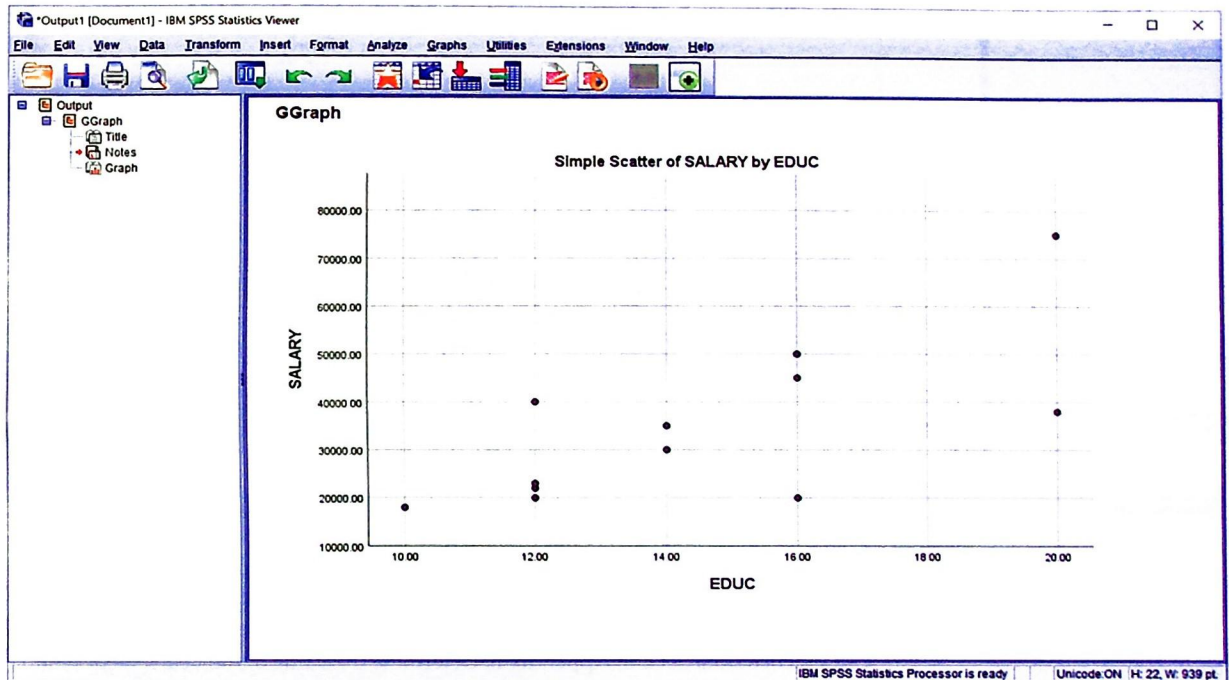
Section 4.2

Use Practice Data Set 1 in Appendix B. After you have entered the data, first construct a histogram that represents the mathematics skills scores and displays a normal curve, and then construct a bar chart that represents the frequencies for the variable AGE.



Section 4.4

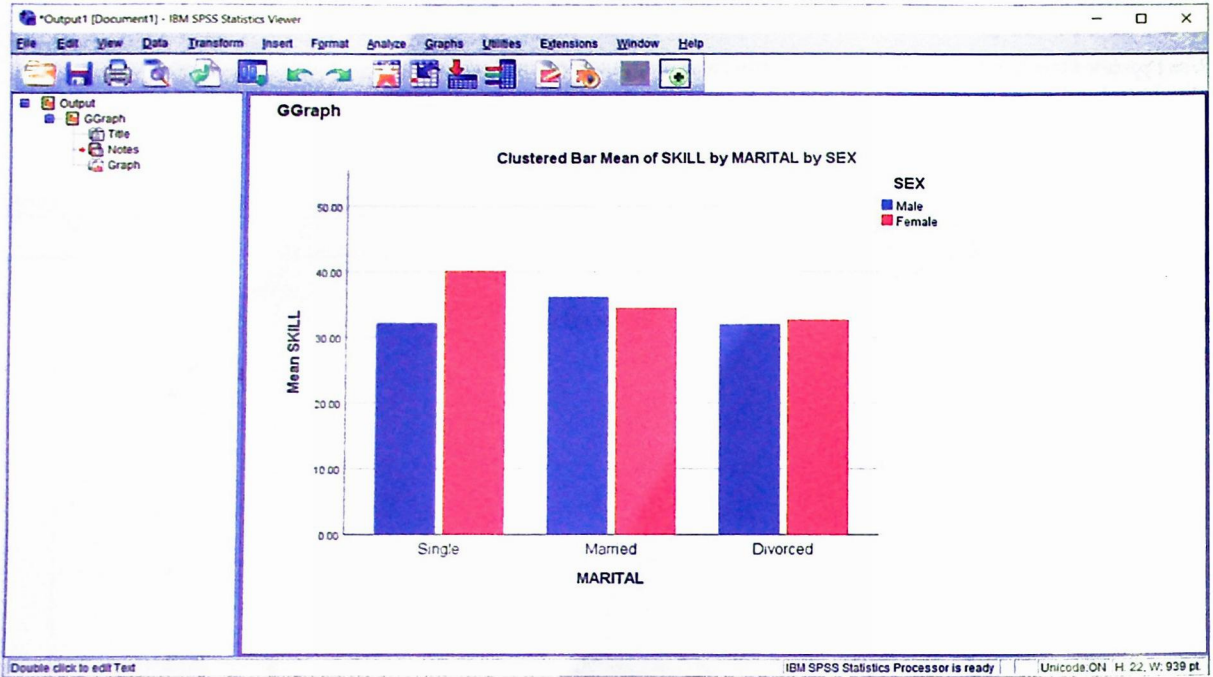
Use Practice Data Set 2 in Appendix B. Construct a scatterplot to examine the relationship between SALARY and EDUCATION.



Note: It would also be acceptable if the student assigned salary to the X-axis and education to the Y-axis.

Section 4.5

Use Practice Data Set 1 in Appendix B. Construct a clustered bar graph examining the relationship between MATHEMATICS SKILLS scores (as the **dependent variable**) and MARITAL STATUS and SEX (as **independent variables**). Make sure you classify both SEX and MARITAL STATUS as nominal variables.



Section 5.1

Use Practice Data Set 2 in Appendix B. Determine the value of the Pearson correlation coefficient for the relationship between SALARY and YEARS OF EDUCATION, and phrase your results.

Correlations

		SALARY	EDUC
SALARY	Pearson Correlation	1	.714**
	Sig. (2-tailed)		.009
	N	12	12
EDUC	Pearson Correlation	.714**	1
	Sig. (2-tailed)	.009	
	N	12	12

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

A Pearson correlation coefficient was calculated for the relationship between subjects' educations and salaries. A strong positive correlation was found ($r(10) = .714, p = .009$), indicating a significant linear relationship between the two variables. Better-educated individuals tended to be paid more.

Section 5.2

Use Practice Data Set 2 in Appendix B. Determine the strength of the relationship between salary and job classification by calculating the Spearman ρ correlation.

IBM SPSS Statistics Processor is ready | Unicode ON | H: 84, W: 936 pt

Nonparametric Correlations				
Correlations				
			SALARY	CLASSIFY
Spearman's rho	SALARY	Correlation Coefficient	1.000	.681*
		Sig. (2-tailed)		.015
		N	12	12
CLASSIFY		Correlation Coefficient	.681*	1.000
		Sig. (2-tailed)	.015	
		N	12	12

*. Correlation is significant at the 0.05 level (2-tailed).

A Spearman ρ correlation coefficient was calculated for the relationship between the subjects' salaries and their job classifications. A strong positive correlation was found ($\rho(10) = .681, p = .015$), indicating a significant relationship between the two variables. Subjects with higher job classifications tended to be paid more.

Section 5.3

Use Practice Data Set 2 in Appendix B. If we want to predict salary from years of education, what salary would you predict for someone with 12 years of education? What salary would you predict for someone with a college education (16 years)?

Regression

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	EDUC ^b		Enter

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

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.714 ^a	.510	.460	12200.14991

a. Predictors: (Constant), EDUC

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1546230088	1	1546230088	10.388	.009 ^b
	Residual	1488436578	10	148843657.8		
	Total	3034666667	11			

a. Dependent Variable: SALARY
b. Predictors: (Constant), EDUC

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		t	Sig.
		B	Std. Error	Beta			
1	(Constant)	-18970.501	17010.145			-1.115	.291
	EDUC	3699.115	1147.694	.714		3.223	.009

a. Dependent Variable: SALARY

$$\text{Salary}' = -18970.5 + 12(3699.115) = \$25,418.88$$

$$\text{Salary}' = -18970.5 + 16(3699.115) = \$40,215.34$$

A simple linear regression was calculated to predict a participant's salary on the basis of education level. A significant regression equation was found ($F(1,10) = 10.388, p = .009$), with an R^2 of .510. Participant's predicted salary is equal to $-18970.5 + 3699.115$ (years of education). Participant's average salary increased by \$3,699 for every year of education.

Section 5.4

Use Practice Data Set 2 in Appendix B. Determine the prediction equation for predicting salary based on education, years of service, and sex. Which variables are significant predictors? If you believe that men were paid more than women, what would you conclude after conducting this analysis?

$$\text{Salary}' = -46257.7 + 4175.856(\text{Education}) + 8856.781(\text{Sex}) + 795.054(\text{Years of Service})$$

Only education is a significant predictor.

When controlling for education and years of service, men do not get paid significantly more than women do.

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	SEX, YOS, EDUC ^b		Enter

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

Model Summary

Model	R	R Square	Adjusted R Square	Std Error of the Estimate
1	.813 ^a	.661	.534	11334.16409

a. Predictors: (Constant), SEX, YOS, EDUC

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2006960463	3	668986820.8	5.208	.028 ^b
	Residual	1027706204	8	128463275.5		
	Total	3034666667	11			

a. Dependent Variable: SALARY
b. Predictors: (Constant), SEX, YOS, EDUC

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-46257.655	25544.945		-1.811	.108
	EDUC	4175.856	1232.166	.806	3.389	.010
	YOS	795.054	538.159	.307	1.477	.178
	SEX	8856.781	7501.024	.278	1.181	.272

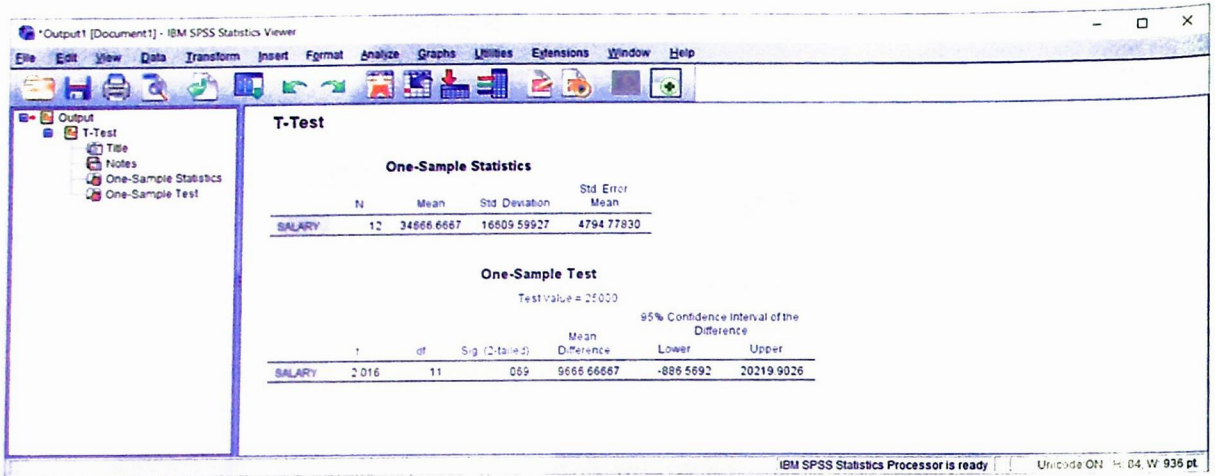
a. Dependent Variable: SALARY

Note: At this point, you would repeat the analysis using only the significant predictors to obtain your final answer.

Section 6.2

The mean salary in the United States is a hypothetical average of \$25,000. Determine if the average salary of the participants in Practice Data Set 2 in Appendix B is significantly greater than this value. Note that this is a one-tailed hypothesis.

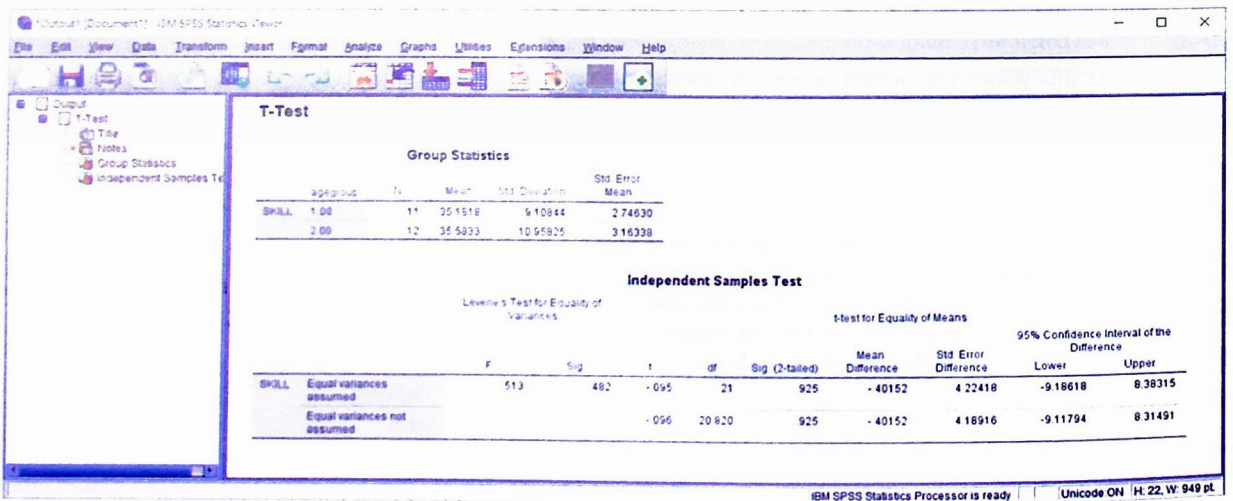
Because this is a one-tailed test, we take the significance level given and divide it by 2. Thus, we have a p of .035, and we conclude that the sample mean is significantly greater than the population mean.



A single-sample t test was calculated to determine if the average salary of our sample is significantly higher than \$25,000. A significant difference was found ($t(11) = 2.016, p = .035$). The sample had a significantly higher average salary ($M = \$34,666.67, sd = \$16,609.60$) than the population.

Section 6.3

Use Practice Data Set 1 in Appendix B to solve this problem. We believe that young individuals have lower mathematics skills than older individuals. We would test this hypothesis by comparing participants 25 or younger (the “young” group) with participants 26 or older (the “old” group). Hint: You may need to create a new variable that represents each age group. See Chapter 2 for help.

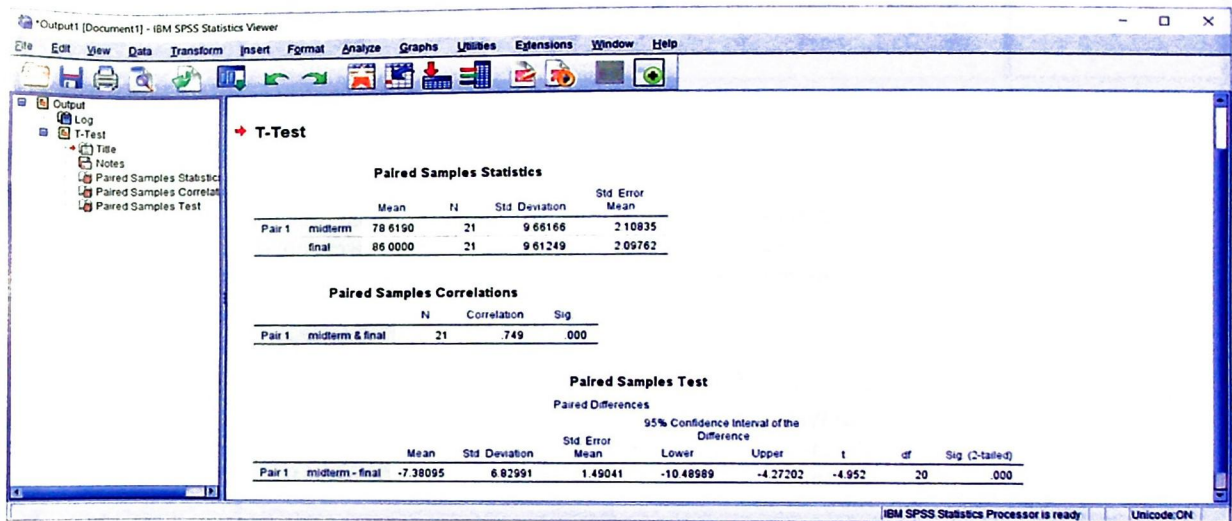


There is no significant difference. Note that we use $.925/2 = .463$ as the actual significance level because this is a one-tailed test.

An independent-samples t test was calculated to determine whether the math skills of subjects 25 or younger were lower than the skills of those 26 or older. No significant difference was found ($t(21) = -.095, p = .463$). The math skills of the younger group ($M = 35.18, sd = 9.11$) were not significantly lower than the math skills of the older group ($M = 35.58, sd = 10.96$).

Section 6.4

Use the same GRADES.sav data file, and compute a paired-samples t test to determine if scores increased from midterm to final.



T-Test

Paired Samples Statistics

	Mean	N	Std. Deviation	Std. Error Mean
Pair 1: midterm	78.6190	21	9.66166	2.10835
final	86.0000	21	9.61249	2.09762

Paired Samples Correlations

	N	Correlation	Sig.
Pair 1: midterm & final	21	.749	.000

Paired Samples Test

Paired Differences

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	midterm - final	-7.38095	6.82991	1.49041	-10.46989	-4.27202	-4.952	20	.000

A paired-samples t test was calculated to determine if scores increased from midterm to final. A significant increase was found ($t(20) = -4.952, p < .001$). The final scores were significantly higher ($M = 86.00, sd = 9.61$) than the midterm scores ($M = 78.62, sd = 9.66$).

Section 7.2

Use Practice Data Set 1 in Appendix B. Determine if the average math scores of single, married, and divorced participants are significantly different. Write a statement of results.

Oneway

Descriptives

SKILL

95% Confidence Interval for Mean

	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Single	12	36.1667	9.33063	2.69352	30.2393	42.0951	19.00	47.00
Married	7	35.7143	12.31143	4.65328	24.3281	47.1005	24.00	59.00
Divorced	4	32.5000	9.00000	4.50000	18.1790	46.8210	20.00	40.00
Total	23	35.3913	9.68911	2.06202	31.1149	39.6677	19.00	59.00

ANOVA

SKILL

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	41.383	2	20.692	.196	.823
Within Groups	2110.095	20	105.505		
Total	2151.478	22			

IBM SPSS Statistics Processor is ready | Unicode ON | H 27, 12 10:10:01

A one-way ANOVA was calculated comparing the math scores of subjects who differed in marital status. No significant differences were found ($F(2,20) = .196$, $p = .823$). Single subjects ($M = 36.17$, $sd = 9.33$) were not significantly different from married subjects ($M = 35.71$, $sd = 12.31$) or divorced subjects ($M = 32.50$, $sd = 9.00$).

Section 7.3

Use Practice Data Set 2 in Appendix B. Determine if salaries are influenced by sex, job classification, or an **interaction** between sex and job classification. Write a statement of results.

Output1 [Document1] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Univariate Analysis of Variance
 - Title
 - Notes
 - Between-Subjects Factor
 - Descriptive Statistics
 - Tests of Between-Subject

Univariate Analysis of Variance

Between-Subjects Factors

	Value Label	N
SEX	1.00 Male	6
	2.00 Female	6
CLASSIFY	1.00 Clerical	4
	2.00 Technical	3
	3.00 Professional	5

Descriptive Statistics

Dependent Variable: SALARY

SEX	CLASSIFY	Mean	Std. Deviation	N
Male	Clerical	23000.0000		1
	Technical	32500.0000	3535.53391	2
	Professional	44333.3333	28041.63571	3
	Total	36833.3333	19913.98169	6
Female	Clerical	20000.0000	2000.00000	3
	Technical	40000.0000		1
	Professional	47500.0000	3535.53391	2
	Total	32500.0000	14110.27994	6
Total	Clerical	20750.0000	2217.35578	4
	Technical	35000.0000	5000.00000	3
	Professional	45600.0000	19982.49234	5
	Total	34666.6667	16609.59927	12

Tests of Between-Subjects Effects

Dependent Variable: SALARY

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1429000000 ^a	5	285800000.0	1.048	.460
Intercept	1.172E+10	1	1.172E+10	43.809	.001
SEX	16030303.03	1	16030303.03	.060	.815
CLASSIFY	1100779193	2	550389596.6	2.057	.209
SEX * CLASSIFY	39887473.46	2	19943736.73	.075	.929
Error	1605666667	6	267611111.1		
Total	1.746E+10	12			
Corrected Total	3034666667	11			

^a R Squared = .471 (Adjusted R Squared = .030)

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A 2 (sex) \times 3 (job classification) between-subjects ANOVA was calculated comparing the salaries of men and women of different job classifications. No significant differences were found. The main effect for sex was not significant ($F(1,6) = .060$, $p = .815$). The main effect for job classification was not significant ($F(2,6) = 2.057$, $p = .209$). The sex \times job classification interaction was not significant ($F(2,6) = .075$, $p = .929$).

Section 7.4

Use Practice Data Set 3 in Appendix B. Determine if the anxiety level of participants changed over time (regardless of which treatment they received) using a one-way repeated-measures ANOVA and protected dependent t tests. Write a statement of results.

IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output Log
General Linear Model
Title
Notes
Within-Subjects Factors
Descriptive Statistics
Multivariate Tests
Mauchly's Test of Sphericity
Tests of Within-Subjects
Tests of Within-Subjects
Tests of Between-Subjects

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

time	Dependent Variable
1	ANXPRE
2	ANX1HR
3	ANX4HR

Descriptive Statistics

	Mean	Std. Deviation	N
ANXPRE	8.2000	1.37321	15
ANX1HR	6.0667	2.01660	15
ANX4HR	5.4000	2.22967	15

Multivariate Tests^a

Effect	Value	F	Hypothesis df	Error df	Sig.	
time	Pillai's Trace	.752	19.701 ^b	2.000	13.000	.000
	Wilks' Lambda	.248	19.701 ^b	2.000	13.000	.000
	Hotelling's Trace	3.031	19.701 ^b	2.000	13.000	.000
	Roy's Largest Root	3.031	19.701 ^b	2.000	13.000	.000

^a Design: Intercept
Within Subjects Design: time

^b Exact statistic

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
time	.924	1.029	2	.598	.929	1.000	.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: time

^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.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	
time	Sphericity Assumed	64.178	2	32.089	16.694	.000
	Greenhouse-Geisser	64.178	1.659	34.531	16.694	.000
	Huynh-Feldt	64.178	2.000	32.089	16.694	.000
	Lower-bound	64.178	1.000	64.178	16.694	.001
Error(time)	Sphericity Assumed	53.822	28	1.922		
	Greenhouse-Geisser	53.822	26.020	2.069		
	Huynh-Feldt	53.822	28.000	1.922		
	Lower-bound	53.822	14.000	3.844		

IBM SPSS Statistics Processor is ready | Unicode ON | H 22, W 1011 pt

A one-way repeated-measures ANOVA was calculated to determine whether anxiety changed over time. A significant effect was found ($F(2,28) = 16.694, p < .001$). Anxiety before treatment was higher ($M = 8.20, sd = 1.37$) than at one hour after ($M = 6.07, sd = 2.02$) and at four hours after treatment ($M = 5.40, sd = 2.23$).

Section 7.5

Use Practice Data Set 3 in Appendix B. Determine if anxiety levels changed over time for each of the treatment (CONDITION) types. How did time change anxiety levels for each treatment? Write a statement of results.

*Output2 [Document2] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- General Linear Model
 - Title
 - Notes
 - Within-Subjects Factors
 - Between-Subjects Factors
 - Descriptive Statistics
 - Multivariate Tests
 - Mauchly's Test of Sphericity
 - Tests of Within-Subjects Independence
 - Tests of Within-Subjects Homogeneity of Variance
 - Tests of Between-Subjects Independence

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

time	Dependent Variable
1	ANXPRE
2	ANX1HR
3	ANX4HR

Between-Subjects Factors

CONDIT	Value Label	N
1.00	Placebo	5
2.00	Valium	5
3.00	Experimental Drug	5

Descriptive Statistics

CONDIT	Mean	Std. Deviation	N
ANXPRE Placebo	8.2000	1.30384	5
ANXPRE Valium	8.4000	1.51658	5
ANXPRE Experimental Drug	8.0000	1.58114	5
ANXPRE Total	8.2000	1.37321	15
ANX1HR Placebo	7.4000	1.51658	5
ANX1HR Valium	4.2000	1.30384	5
ANX1HR Experimental Drug	6.6000	1.81659	5
ANX1HR Total	6.0667	2.01660	15
ANX4HR Placebo	7.6000	1.51658	5
ANX4HR Valium	5.4000	1.51658	5
ANX4HR Experimental Drug	3.2000	83666	5
ANX4HR Total	5.4000	2.22967	15

Multivariate Tests^a

Effect	Value	F	Hypothesis df	Error df	Sig.	
time	Pillai's Trace	.941	87.375 ^b	2.000	11.000	.000
	Wilks' Lambda	.059	87.375 ^b	2.000	11.000	.000
	Hotelling's Trace	15.886	87.375 ^b	2.000	11.000	.000
	Roy's Largest Root	15.886	87.375 ^b	2.000	11.000	.000
time * CONDIT	Pillai's Trace	1.657	29.021	4.000	24.000	.000
	Wilks' Lambda	.027	27.909 ^b	4.000	22.000	.000
	Hotelling's Trace	10.643	26.608	4.000	20.000	.000
	Roy's Largest Root	7.072	42.432 ^c	2.000	12.000	.000

a. Design: Intercept + CONDIT
Within Subjects Design: time

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

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IBM SPSS Statistics Viewer

Mauchly's Test of Sphericity^a

Measure	MEASURE_1	Approx. Chi-Square	df	Sig.	Greenhouse-Geisser	Epsilon ^b	Lower-bound
time	996	043	2	.979	.996	1.000	.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 * CONDIT
Within Subjects Design time

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.

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	64.178	2	32.089	90.250	.000
	Greenhouse-Geisser	64.178	1.992	32.214	90.250	.000
	Huynh-Feldt	64.178	2.000	32.089	90.250	.000
	Lower-bound	64.178	1.000	64.178	90.250	.000
time * CONDIT	Sphericity Assumed	45.289	4	11.322	31.844	.000
	Greenhouse-Geisser	45.289	3.984	11.366	31.844	.000
	Huynh-Feldt	45.289	4.000	11.322	31.844	.000
	Lower-bound	45.289	2.000	22.644	31.844	.000
Error(time)	Sphericity Assumed	8.533	24	.356		
	Greenhouse-Geisser	8.533	23.907	.357		
	Huynh-Feldt	8.533	24.000	.356		
	Lower-bound	8.533	12.000	.711		

Tests of Within-Subjects Contrasts

Source	time	Type III Sum of Squares	df	Mean Square	F	Sig.
time	Linear	58.800	1	58.800	176.400	.000
	Quadratic	5.378	1	5.378	14.235	.003
time * CONDIT	Linear	22.200	2	11.100	33.300	.000
	Quadratic	23.089	2	11.544	30.559	.000
Error(time)	Linear	4.000	12	.333		
	Quadratic	4.533	12	.378		

Tests of Between-Subjects Effects

Source	Transformed Variable	Average	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept			1933.889	1	1933.889	341.945	.000
CONDIT			31.244	2	15.622	2.762	.103
Error			67.867	12	5.656		

IBM SPSS Statistics Processor is ready Unicode ON H: 22, W: 1032 pt

A 3 (TIME) × 3 (CONDITION) mixed-design ANOVA was calculated to determine if either time or type of treatment influenced anxiety levels. The main effect for type of treatment was not significant ($F(2,12) = 2.762, p = .103$). The main effect for time was significant ($F(2,24) = 90.25, p < .001$). The TIME × CONDITION interaction was also significant ($F(4,24) = 31.844, p < .001$).

Section 7.6

Use Practice Data Set 2 in Appendix B. Determine if salaries are different for males and females. Repeat the analysis, statistically controlling for years of service. Write a statement of results for each. Compare and contrast your two answers.

SPSS Statistics Viewer window showing the results of a T-Test and Univariate Analysis of Variance (ANOVA) for the variable SALARY.

T-Test

Group Statistics

SEX	N	Mean	Std. Deviation	Std. Error Mean
SALARY Male	6	36833.3333	19913.98169	8129.84898
SALARY Female	6	32500.0000	14110.27994	5760.48766

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means				95% Confidence Interval of the Difference		
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
SALARY	Equal variances assumed	.011	.918	.435	10	.673	4333.33333	9963.82345	-17867.44881	26534.11548
	Equal variances not assumed			.435	9.010	.674	4333.33333	9963.82345	-18202.64367	26869.31033

Univariate Analysis of Variance

Between-Subjects Factors

SEX	Value Label	N
1.00	Male	6
2.00	Female	6

Descriptive Statistics

SEX	Mean	Std. Deviation	N
Male	36833.3333	19913.98169	6
Female	32500.0000	14110.27994	6
Total	34666.6667	16609.59927	12

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	531486075 ^a	2	265743037.8	.955	.420
Intercept	2506445365	1	2506445365	9.012	.015
YOS	475152741.8	1	475152741.8	1.708	.224
SEX	36118764.53	1	36118764.53	.130	.727
Error	2503180591	9	278131176.8		
Total	1.746E+10	12			
Corrected Total	3034666667	11			

a. R Squared = .175 (Adjusted R Squared = -.008)

Without Controlling for Years of Service

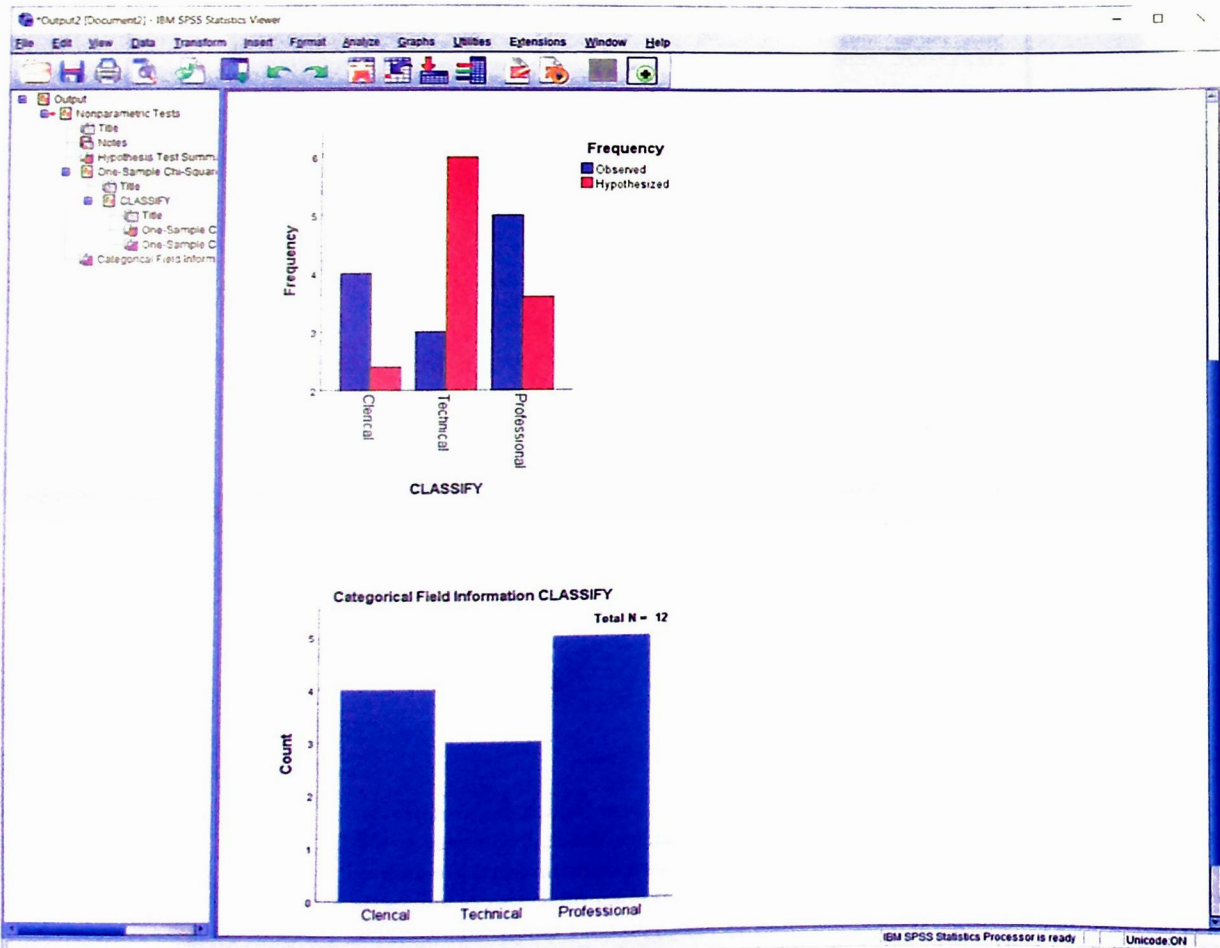
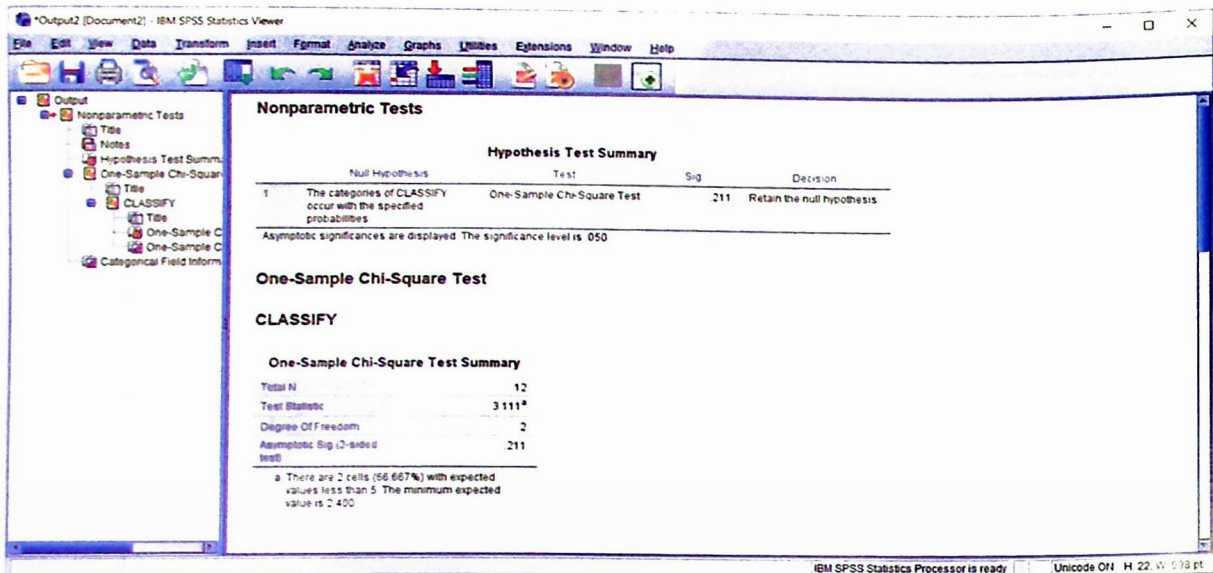
An independent samples t test calculated to determine if the salaries of men and women differ. No significant difference was found ($t(10) = .435, p = .673$). The mean salaries of men are not significantly different from the mean salaries of women.

ANCOVA results

A one-way ANCOVA was calculated to determine if the salaries of men and women are different when controlling for years of service. Years of service was not significantly related to salary ($F(1,9) = 1.708, p = .224$). Salaries did not differ between men and women even when controlling for years of service ($F(1,9) = .130, p = .727$).

Section 8.1

Use Practice Data Set 2 in Appendix B. In the population from which the sample was drawn, 20 percent of employees are clerical, 50 percent are technical, and 30 percent are professional. Determine whether or not the sample drawn conforms to these values. Hint: You will need to *customize expected probabilities* and enter the category values (1, 2, 3) and relative percentages (20, 50, 30). Also, be sure you have entered the variable CLASSIFY as nominal.



A chi-square goodness of fit test was calculated to determine if the sample fit with the hypothesized distribution of 20% clerical, 50% technical, and 30% professional. No significant deviation from the hypothesized values was found ($\chi^2(2) = 3.11, p > .05$). The observed distribution (4/12 clerical, 3/12 technical, 5/12 professional) did not vary significantly from the hypothesized values.

Section 8.2

A researcher wants to know if individuals are more likely to help in an emergency when they are indoors or when they are outdoors. Of 28 participants who were outdoors, 19 helped and 9 did not. Of 23 participants who were indoors, 8 helped and 15 did not. Enter these data, and find out if helping behavior is affected by the environment. The key to this problem is in the data entry. (Hint: How many participants were there, and how many pieces of information do we know about each? Having SPSS give you cell percentages will help you with interpretation of this problem.)

The screenshot shows the IBM SPSS Statistics Data Editor window. The dataset has 51 rows and 2 columns: 'indoor' and 'help'. The data is as follows:

Case	indoor	help
1	00	100
2	00	100
3	00	100
4	00	100
5	00	100
6	00	100
7	00	100
8	00	100
9	00	100
10	00	100
11	00	100
12	00	100
13	00	100
14	00	100
15	00	100
16	00	100
17	00	100
18	00	100
19	00	100
20	00	00
21	00	00
22	00	00
23	00	00
24	00	00
25	00	00
26	00	00
27	00	00
28	00	00
29	100	100
30	100	100
31	100	100
32	100	100
33	100	100
34	100	100
35	100	100
36	100	100
37	100	00
38	100	00
39	100	00
40	100	00
41	100	00
42	100	00
43	100	00
44	100	00
45	100	00
46	100	00
47	100	00
48	100	00
49	100	00
50	100	00
51	100	00

The screenshot shows the IBM SPSS Statistics Viewer interface. The main window displays the following output:

Case Processing Summary

	Valid		Cases Missing		Total	
	N	Percent	N	Percent	N	Percent
indoor * help	51	100.0%	0	0.0%	51	100.0%

indoor * help Crosstabulation

		help			
		00	1 00	Total	
indoor	00	Count	9	19	28
		Expected Count	13.2	14.8	28.0
		% within indoor	32.1%	67.9%	100.0%
		% within help	37.5%	70.4%	54.9%
1 00		Count	15	8	23
		Expected Count	10.8	12.2	23.0
		% within indoor	65.2%	34.8%	100.0%
		% within help	62.5%	29.6%	45.1%
Total		Count	24	27	51
		Expected Count	24.0	27.0	51.0
		% within indoor	47.1%	52.9%	100.0%
		% within help	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	5.545 ^a	1	.019		
Continuity Correction ^b	4.296	1	.038		
Likelihood Ratio	5.640	1	.018		
Fisher's Exact Test				.026	.019
Linear-by-Linear Association	5.436	1	.020		
N of Valid Cases	51				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.82.
b. Computed only for a 2x2 table.

A chi-square test of independence was calculated comparing the frequency of helping behavior for subjects inside and outside. A significant interaction was found ($\chi^2(1) = 5.545, p < .05$). Subjects were more likely to help outside (67.9%) than they were inside (34.8%).

Section 8.3

Use Practice Data Set 1 in Appendix B. Determine if younger participants (< 26) have significantly lower mathematics scores than older participants. (Note: You will need to create a new ordinal variable representing each age group. See Section 2.2 if you need a refresher on how to do that.)

Output2 [Document2] - IBM SPSS Statistics Viewer

File Edit View Data Transform Insert Format Analyze Graphs Utilities Extensions Window Help

Output

- Nonparametric Tests
 - Title
 - Notes
 - Hypothesis Test Summ.
 - Independent-Samples I
 - Title
 - SKILL across ageg
 - Title
 - Independent-S
 - Independent-S
 - Continuous Field Inform
 - Categorical Field Inform

Nonparametric Tests

Hypothesis Test Summary

	Null Hypothesis	Test	Sig	Decision
1	The distribution of SKILL is the same across categories of agegroup	Independent-Samples Mann-Whitney U Test	1.000 ^a	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .050.
^a Exact significance is displayed for this test.

Independent-Samples Mann-Whitney U Test

SKILL across agegroup

Independent-Samples Mann-Whitney U Test Summary

Total N	23
Mann-Whitney U	66.500
Wilcoxon W	144.500
Test Statistic	66.500
Standard Error	16.192
Standardized Test Statistic	.031
Asymptotic Sig. (2-sided test)	.975
Exact Sig. (2-sided test)	1.000

Independent-Samples Mann-Whitney U Test

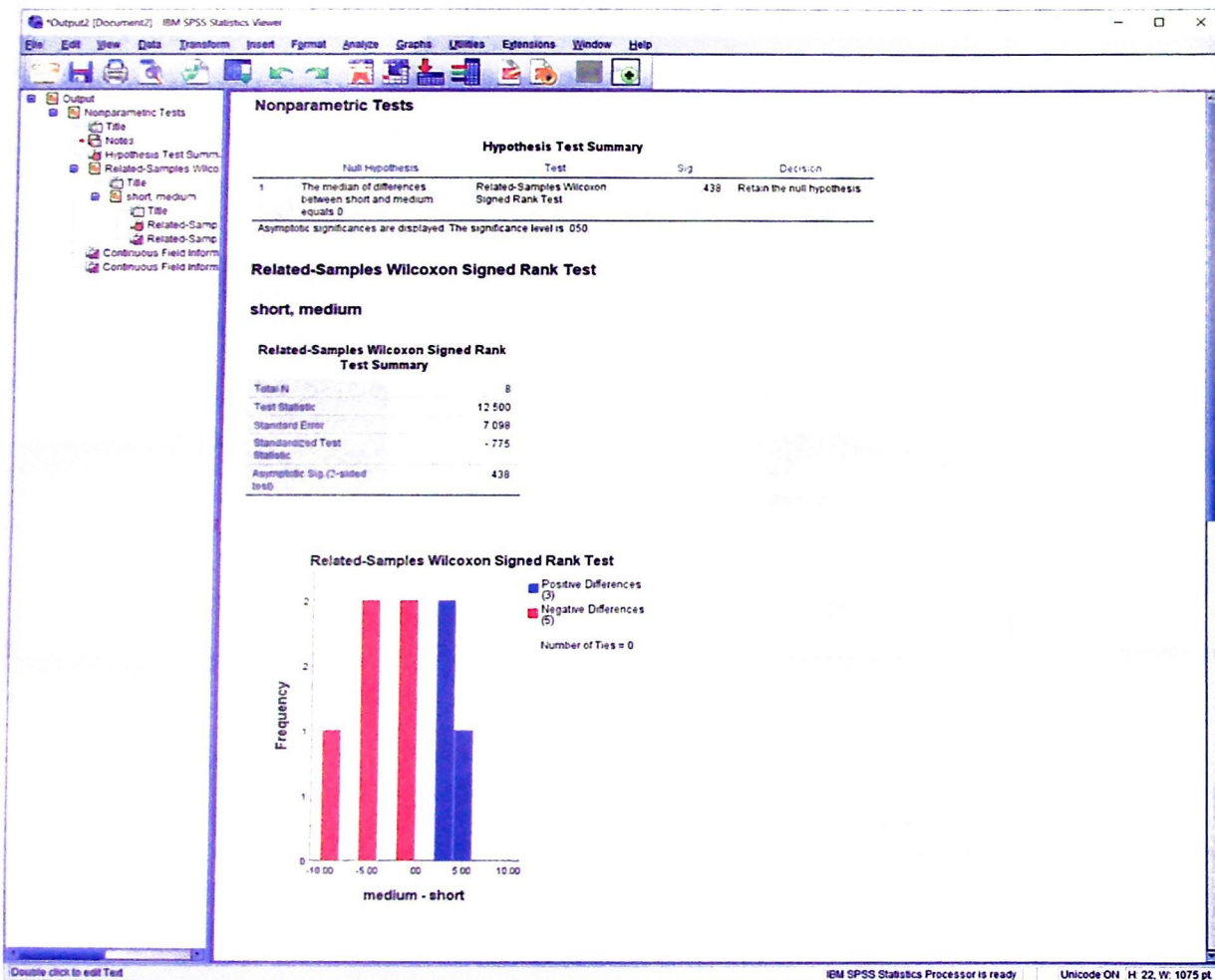
agegroup

Notched box plot showing the distribution of SKILL for two age groups. The left group (N=11, Mean Rank=11.95) has a median around 35. The right group (N=12, Mean Rank=12.04) has a median around 40. The y-axis is labeled SKILL and ranges from 00 to 80.00. The x-axis is labeled Frequency and ranges from -4 to 4.

A Mann-Whitney U test was calculated examining the math skills scores of older and younger subjects. No significant difference was found ($U = 65.5, p > .05$). Younger subjects had a mean rank of 11.95 while older subjects had a mean rank of 12.04.

Section 8.4

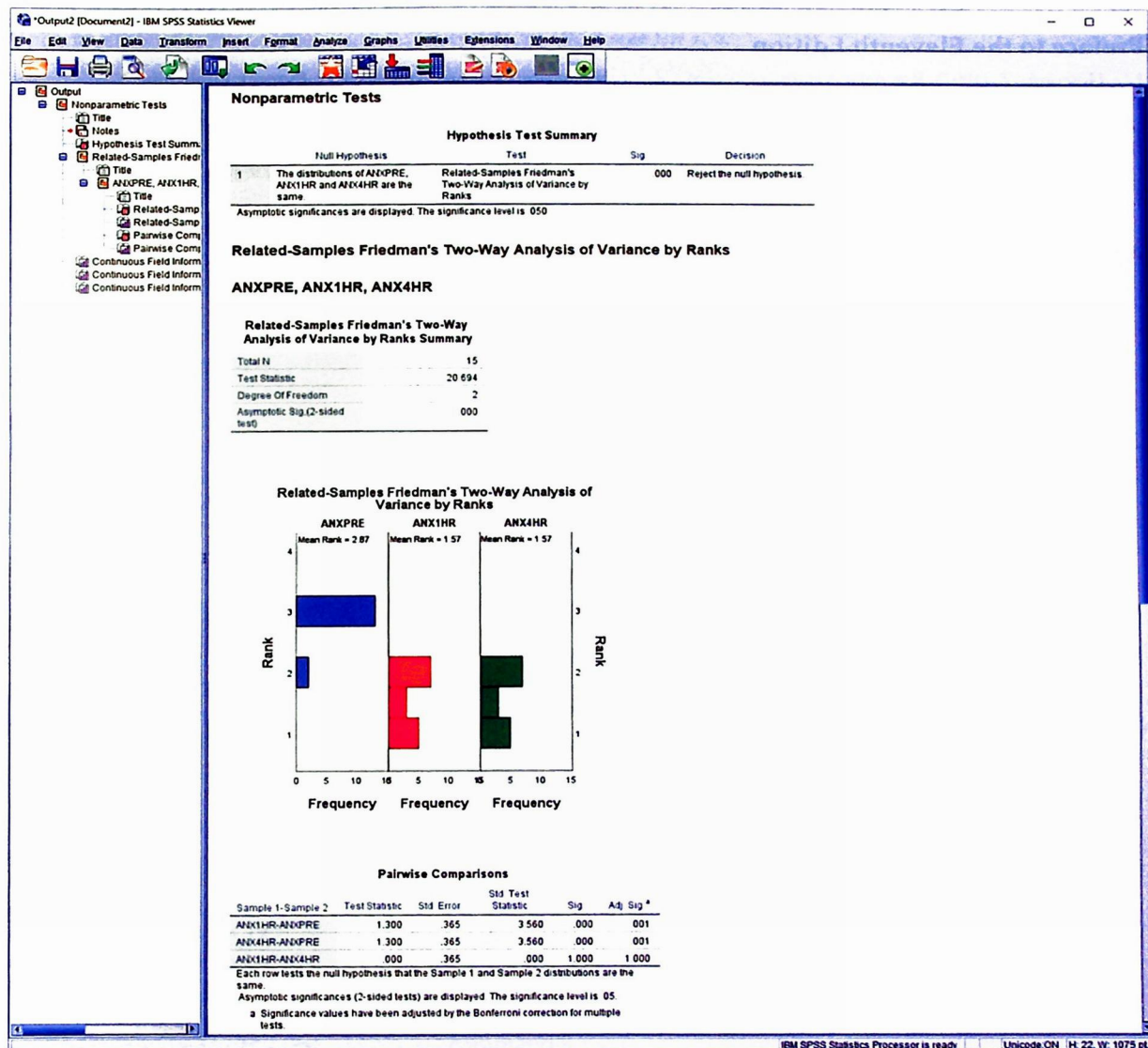
Use the RACE.sav data file to determine whether or not the outcome of short-distance races is different from that of medium-distance races. Phrase your results.



A Wilcoxon test examined the results of medium-distance and short-distance races. No significant difference was found in the results ($Z = -0.775, p > .05$). Medium-distance results were not significantly different from short-distance results.

Section 8.6

Use the data in Practice Data Set 3 in Appendix B. If anxiety is measured on an ordinal scale, determine if anxiety levels changed over time. Phrase your results.



A Friedman test was conducted comparing the average anxiety ranking of subjects before, one hour after, and four hours after treatment. A significant difference was found ($\chi^2(2) = 20.694, p < .05$). Student anxiety was significantly reduced from the pretest value at both one hour and four hours.

Notes

Preface to the Eleventh Edition

- 1 Holcomb, Z. (1997). *Real data: A statistics workbook based on empirical data*. Los Angeles, CA: Pycszak Publishing.

1 Getting Started

- 1 Items that appear in the Glossary in Appendix E are presented in **bold**. *Italics* are used to indicate menu items.
- 2 Depending upon your version of SPSS, it may be displayed as 2.0E + 009.

Appendix A

- 1 Kirk, R. E. (1996). Practical significance: A concept whose time has come. *Educational & Psychological Measurement*, 56, 746–759.
- 2 Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112, 155–159.
- 3 Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum.

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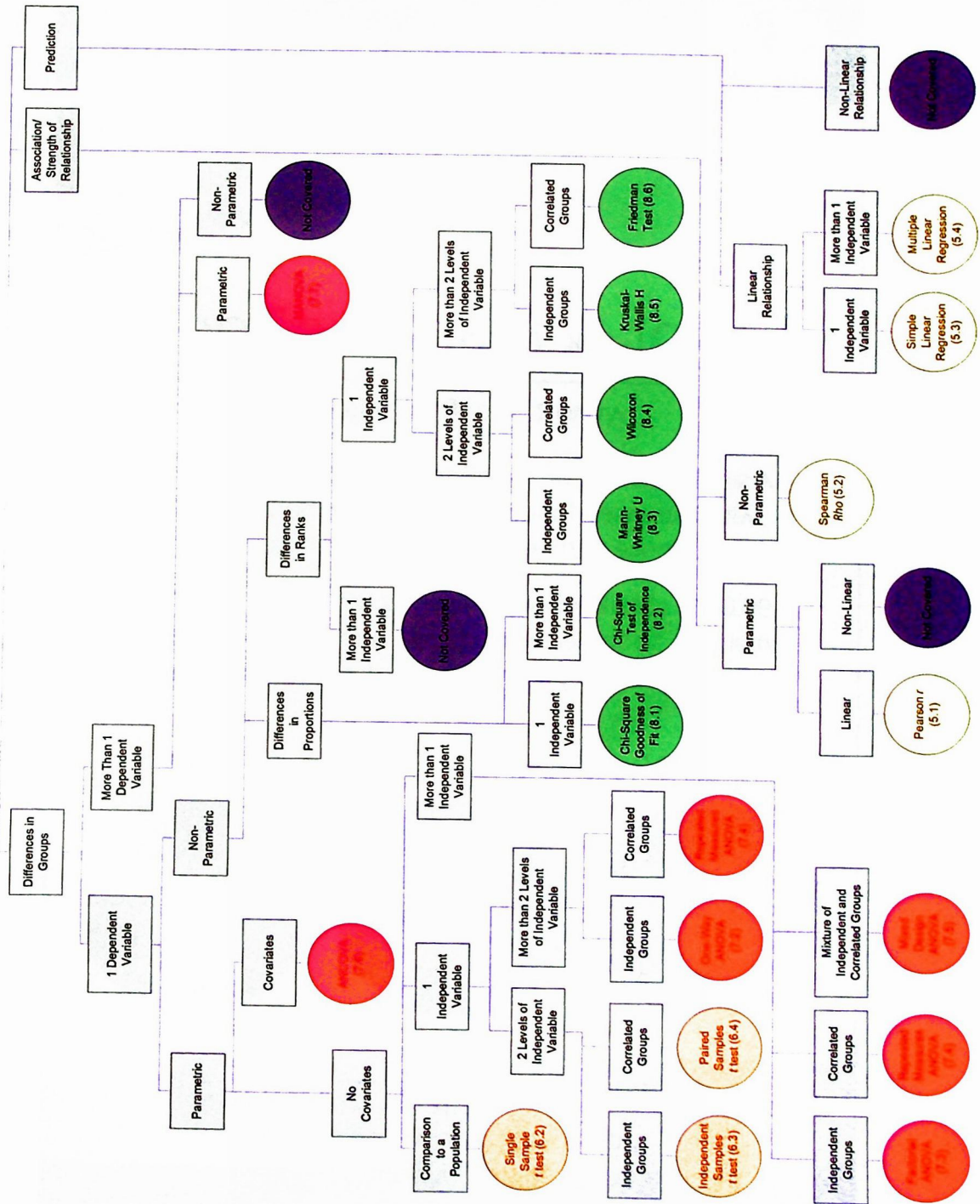
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