The Magic of Pretest/Posttest & Longitudinal Data Analysis 6 Week Webinar Class

CLASS 2:

PRETEST/POSTTEST ANALYSIS

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Pretest/Posttest Analysis

Welcome to **Week 2 Pretest/Posttest Data Analysis** of our 6-week webinar class *The Magic of Pretest/Posttest & Longitudinal Data Analysis*. Recall, *The 7 Steps of Data Analysis* listed below. Notice our focus will be on Steps 3-6 as each pertains to performing Pretest/Posttest Data Analysis.

The 7 Steps of Data Analysis:

1 Study Map

2 Data Entry

3 Check Data Integrity **FOCUS**

4 Univariate Analysis **FOCUS**

5 Bivariate Analysis **FOCUS**

6 Multivariate Analysis **FOCUS**

7 Write-up and Report

Step 3: Check Data Integrity

What we are asking: Are the data appropriate for statistical analysis?

Consider, what is the value of a study if the findings are incorrect? Such a study is more likely to be a threat rather than a contribution to the field of research. Subsequently, it is important to realize that missed checks of data integrity, even minor missed checks, can easily lead to inaccurate statistical findings. Therefore, in this presentation we will make a cursory, yet effective check of all necessary areas of data integrity. Keep in mind, certain aspects of checks of data integrity vary by aspects of the study, including the types of statistical tests employed. In this presentation our checks of data integrity will consider our final multivariate procedures, which are **Multiple Linear Regression (MLR)** and **Repeated Measures General Linear Model (GLM)**. We can estimate that there are 4 areas where data integrity must be checked, which are:

Check 1: Statistical Power (Done in week 1!)

Check 2: Test Assumptions (week 2)

Check 3: Missing Data (week 4)

Check 4: Measurement Tools (week 2)

Notice, *Check 1: Statistical Power* was addressed in week 1. This week, week 2, will address *Check 2: Test Assumptions* and *Check 4: Measurement Tools* for Pretest/Posttest Analysis. *Check 3: Missing Data* will be addressed in week 4.

Why use **Multiple Linear Regression (MLR)** for Pretest/Posttest Analysis?

You will see in our analysis that **Repeated Measures General Linear Model (GLM)** is a statistical procedure designed to examine changes in the outcome variable between timepoints. The procedure is appropriate for both Pretest/Posttest and Longitudinal data analysis. Subsequently, one might wonder why we would also consider using **Multiple Linear Regression (MLR)** as the final multivariate tool in Pretest/Posttest analysis.

In essence, the use of MLR in Pretest/Posttest analysis facilitates the use of **Difference Scores**, which present the outcome variable (i.e., changes in the outcome score from pretest to posttest) in a very effective manner. Again, the outcome variable in this study is not pretest happiness scores nor posttest happiness scores, but the *change in happiness scores from pre to post*. Therefore, if we minus pretest scores from posttest, which will create a **difference score**, that will allow us to view the actual outcome variable in a manner we could not otherwise. To create the difference score in SPSS follow the following steps:

- In SPSS go to: *Transform, Compute Variable*
- Under *Target Variable* enter *differenceprepost*
- Under *Numeric Expression* enter *posttest-pretest*
- Click *OK* or *PASTE* (if *Paste* then run) to produce **Difference Scores**

Since the difference score is a single value (as opposed to the 2 values of pretest scores and posttest scores), which would require a **MLR** for final multivariate analysis. By the way, if we kept the outcome variable as the 2 separate values of pretest and posttest scores, we would use **Repeated Measures GLM** as the final multivariate analysis. *The test assumptions and measurement tool assessment are applicable for both procedures.*

The Range of Difference Scores

Keep in mind, both our pretest and posttest *Happiness* scores are measured on a 1-5 scale (5= More Happy). Thus, the difference score reflecting the most positive change is 4.0 (with a score of 1 at pretest and a 5 at posttest). The most negative change is -4.0 (with a score of 5 at pretest and 1 at posttest). A score of 0 indicates no change in happiness scores from pretest to posttest.

Check 2: Test Assumptions

When performing pretest to posttest analysis, whether employing **MLR** or **Repeated Measure GLM**, we would consider the check assumptions A-F below. These checks can largely be done via the examination of the Pre/Post **Happiness Difference Scores**, in conjunction with the other study variables:

A. Normal Distributions (Normality)

B. Influence of outlier scores

C. Linearity

D. Homoscedasticity

E. Multicollinearity

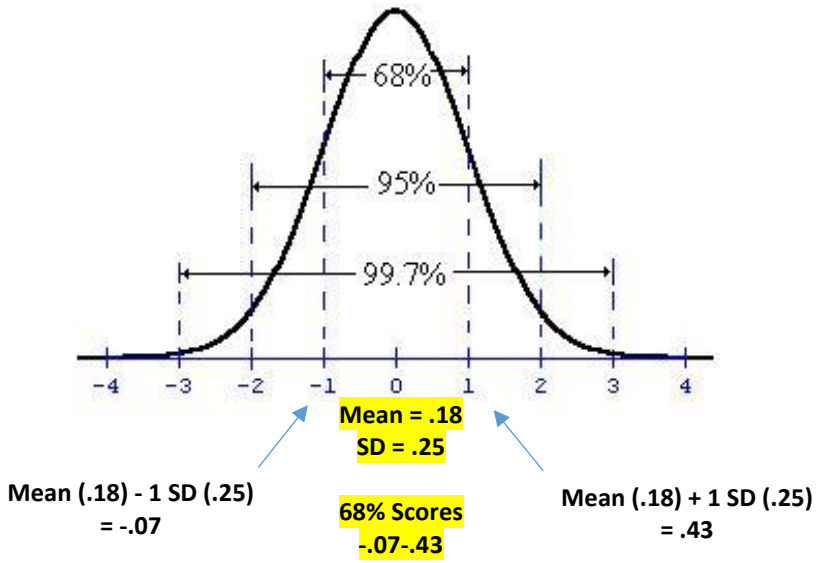
F. Others (Not addressed here)

A. Normal Distribution (Normality)

Parametric tests, such as linear regression, assume that a continuous variable has a distribution of scores that approximates a **normal distribution**. A normal distribution of scores is a theoretical distribution of values that makes a bell shaped symmetrical curve presented in **Figure 1**.

Within this figure, the '0' in the center bottom represents the mean score. The numbers to the left and right of the '0' indicate units of standard deviation, which describe the percentage of cases that will vary from the mean score in 1, 2, 3, and 4 units of standard deviation if a distribution is perfectly normal. For example, we see that 68% of scores will fall within one standard deviation of the mean score. To give these values greater meaning, let's generalize these parameters to the outcome variable in our pretest to posttest study, which is **Happiness Difference Scores**.

Figure 1. A Normal Distribution of Difference Scores



First, notice in the center of the distribution the mean and standard deviation values for the **Happiness Difference Scores** are .18 and .25, respectively.

To identify the score 1 SD below the mean score minus 1 SD (.25) from the mean score (.18), which would be -.07.

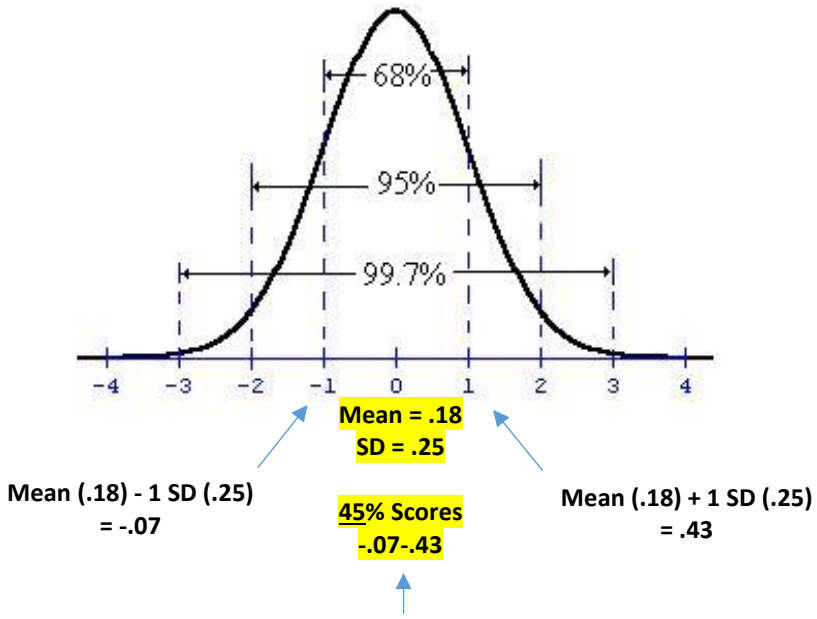
To identify the score 1 SD above the mean score add 1 SD (.25) to the mean score (.18), which would be .43.

Thus, if the distribution of difference scores was normal, 68% of cases should be within the scores -.07 to .43. However, we see within **Figure 2** that the **Actual Distribution of Happiness Difference Scores** reflects that there are **45% Scores** between **1 SD (-.07-.43)** of the mean score. Now we must identify if the distribution of scores is still approximately normal even though the distribution is not perfectly normal.

Testing for a Normal Distribution

There are several methods for testing if a distribution of scores is approximately normal. One common method is to observe if the skewness (peak in the center) of the distribution is 3 times the Standard Error of the skew. Additionally, you must determine if the kurtosis (distribution of scales within the tails) of the distribution is 3 times the Standard Error of the skew.

Figure 2. Actual Distribution of Happiness Difference Scores



Is **45% of Scores** within 1 SD of the mean score approximately normal?

Computing Skewness & Kurtosis

In order to compute the skewness and kurtosis (as well as the standard error of each) in SPSS go to:

- *Analyze, Descriptive Statistics, Frequencies*
- Enter *variable* e.g., *differenceprepost*
- Under *Statistics* check *skewness* & *Kurtosis*
- Click *OK* or *PASTE* (if *Paste* then run)

Computing Skewness & Kurtosis/Standard Error Ratio

The output in SPSS indicates that the skewness and kurtosis, as well as the respective standard error of each is:

Skewness	.68
Std. Error of Skewness	.24
Kurtosis	-.64
Std. Error of Kurtosis	.48

If we divide the skewness and kurtosis by their respective standard error we see the skewness/standard error of the skewness is 2.83 (**.68/.24 = 2.83**). We see the value of the skewness is not three times the standard error, so we could call the distribution approximately normal. Likewise, we see the ratio of the kurtosis to the standard error of the kurtosis is 1.33 (**-.64/.48 = 1.33**). We see the value of the kurtosis is not three times the standard error, so we could call the distribution approximately normal.

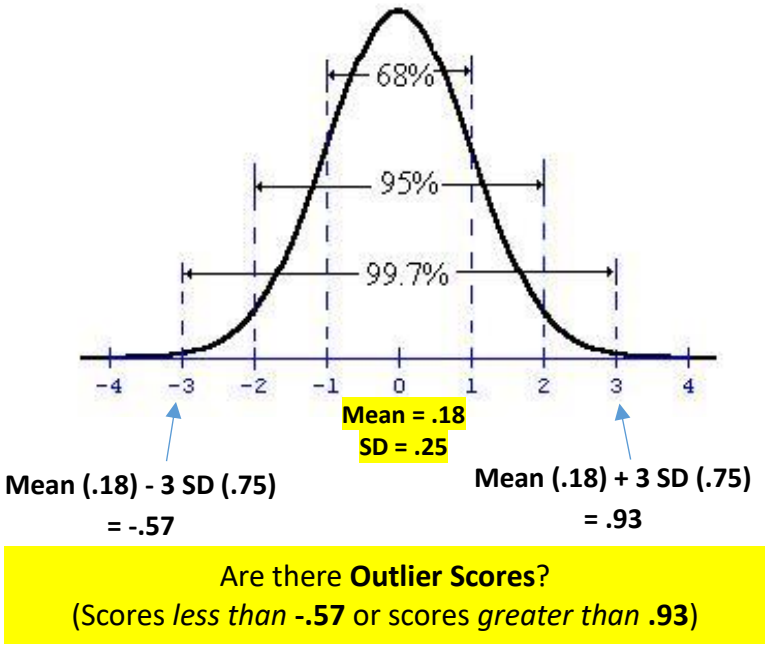
B. Influence of Outlier Scores

Next, we want to assure that if the distribution contains outlier scores, that those scores do not have an undue influence in study findings. That means we want to be sure that the findings of the study will not change (e.g., in terms of statistical significance) based upon outlier scores.

The first step in this process is to identify if there are outlier scores in the distribution. Toward this, we might define outlier scores as any scores 3 SDs above or below mean score. If there are outlier scores, test for their impact on study findings by running the same statistical test with and without score and note if the outlier scores change the findings (are results statistically significant with the outlier, but not without it or vice versa?). First, to identify if the distribution contains outlier scores by computing the mean and standard deviation of the distribution in SPSS by going to:

- *Analyze, Descriptive Statistics, Frequencies*
- Enter *variable* e.g., *differenceprepost*, in the right-hand column
- Under *Statistics* check *mean* & *standard deviation*, then Continue
- Click *OK* or *PASTE* (if *Paste* then run)

Figure 3 Outlier *Happiness Difference Scores* (>3 SD) in the distribution



Check frequency table

Next, check your Frequency Table and observe if there are any scores outside the 3 SD outlier interval.

Figure 4. Frequency Table for Pretest to Posttest Difference Scores

Pretest to Posttest Difference Scores

		Frequency	Percent	Valid Percent	Cumulative Percent
Outlier Low **<-.57**					
	-.20	1	1.0	1.0	1.0
	-.15	1	1.0	1.0	2.0
>.93	between	btw	btw	btw	btw
	.70	1	1.0	1.0	98.0
Outlier High	.75	1	1.0	1.0	99.0
	.80	1	1.0	1.0	100.0

Figure 4. presents the **Frequency Table for Pretest to Posttest Difference Scores**. We see the lowest score is -.20, which is greater than the lower bound value of -.57, which indicates there is not an outlier score that is significantly below the mean score. Simultaneously, we see the highest score is .80, which is less than the upper bound value of .93, which indicates there is not an outlier score that is significantly above the mean score. Thus, in the distribution of **Pretest to Posttest Happiness Difference Scores**, there are no outlier scores that might have an undue influence on study findings.

However, to reiterate, if there was an outlier score(s), we would test the influence of the score on results by creating a version of the variable with and without the outlier score. Then we would conduct the same statistical test using the version with & without the outlier score. Lastly, we would observe if findings differ between the 2 tests (e.g., statistical significance)?

If the findings differ between the 2 tests (e.g., statistical significance) this may indicate the outlier has an undue influence on analysis. We would consider excluding the case from analysis as this single score is driving findings. If findings do not differ, we might consider leaving the score in analysis as the outlier score does not seem to present an undue influence on findings.

C. Linearity

Another test assumption for *Multiple Linear Regression* is that variable scores evidence a linear relationship or linearity. The linear relationship may be *positive*, as in **Figure 5**, where as *Income level* increases, then *Happiness Difference Scores* also increase. The linear relationship may be *negative*, as in **Figure 6**, where as *Income level* increases, then *Happiness Difference Scores* decrease.

D. Homoscedasticity

A further test assumption of MLR is homoscedasticity, which refers to a homogeneity of variance where data points (residuals) are spread out evenly between variables. Specifically, this assumption addresses if there is an equal variance of residuals of the IV (e.g., Income Level) at different levels of the DV (e.g., Difference Scores).

Figure 5 A Perfect *Positive* Linear Relationship (Correlation)

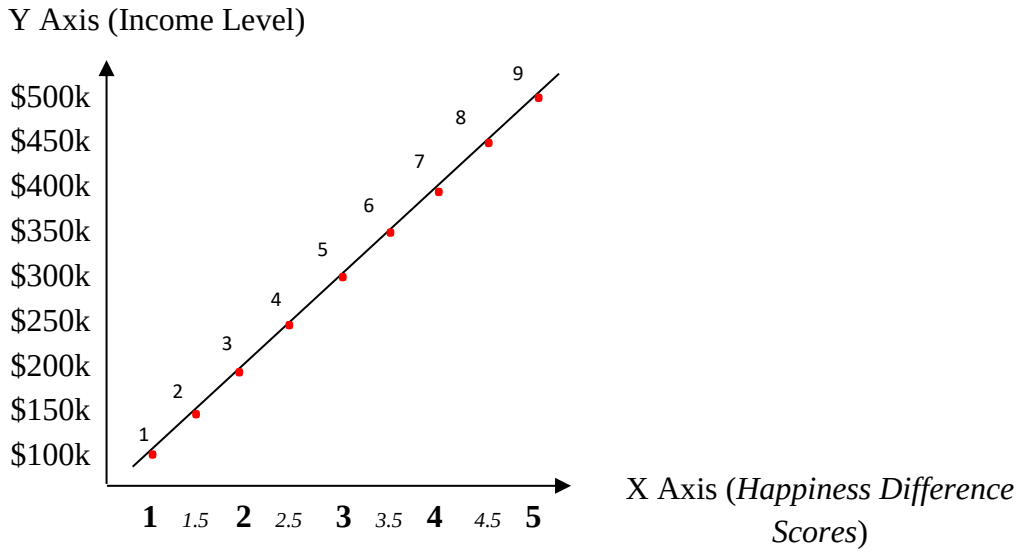
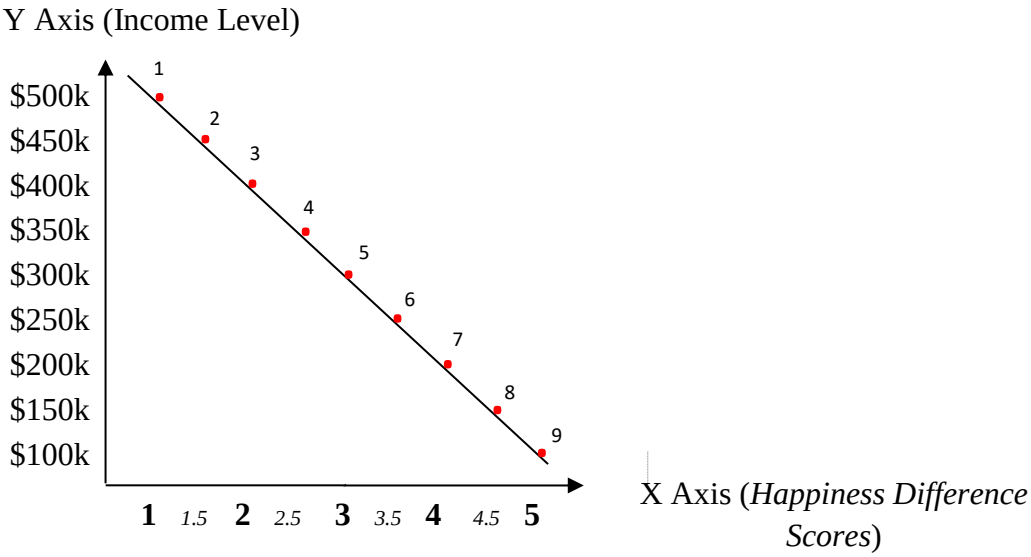


Figure 6 A Perfect *Negative* Linear Relationship (Correlation)



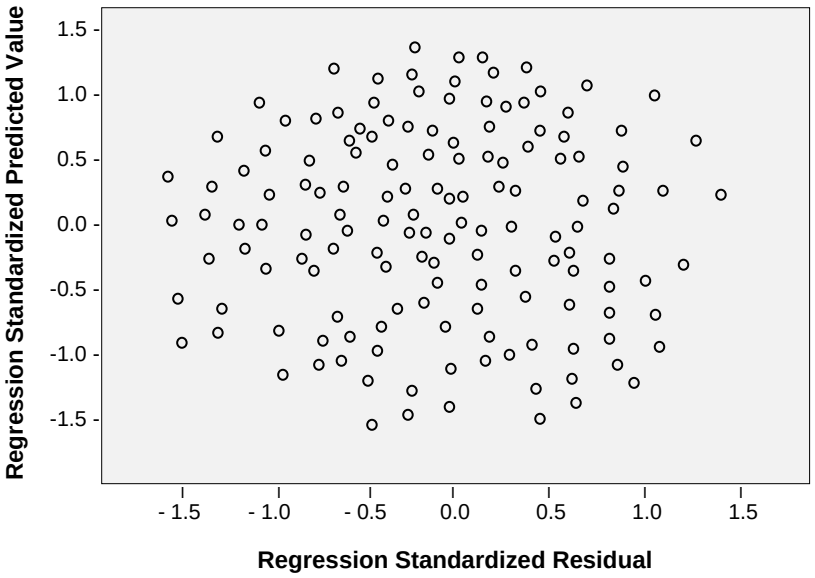
Testing Linearity/Homoscedasticity

The assumption of Linearity and Homoscedasticity may be examined through plotting the residuals of the variables (*ZRESID* by *ZPRED*) in a scatterplot. This can be done in SPSS in the linear regression function, where you would go to:

- *Analyze*, *Regression*, *Linear*
- Enter *dep. variable* e.g., *differenceprepost*
- Enter *Ind. variable(s),* e.g., *income level, etc.*
- Click Plots, put *ZRESID* & *ZPRED* in Y & X boxes, click *Continue*
- Click *OK* or *PASTE* (if *Paste* then run)

Figure 7 presents the ZPRED by ZRESID Scatterplot reflecting *Linearity* and *Homoscedasticity*. Good homoscedasticity and linearity is indicated by the random dispersion of dots around zero.

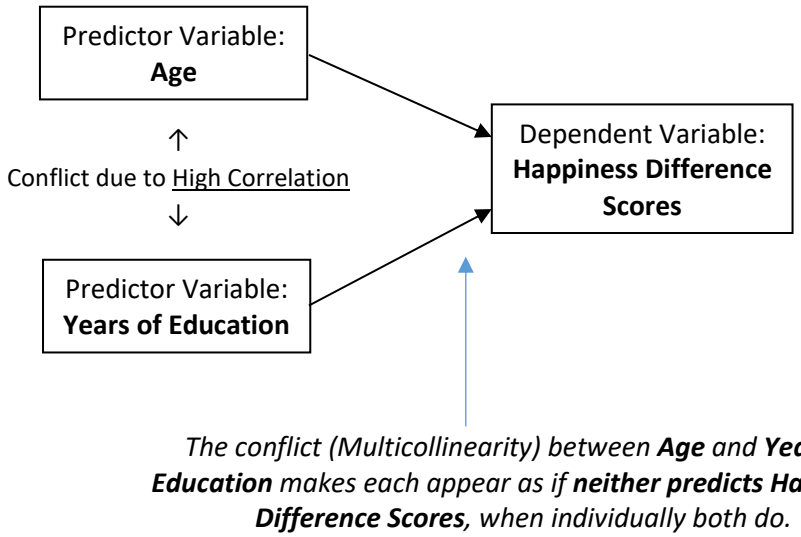
Figure 7 ZPRED by ZRESID Scatterplot



E. Multicollinearity

Multicollinearity is a necessary check when conducting a regression model with multiple predictors. Multicollinearity occurs when predictor variables are correlated at too high a level. For example, as presented in **Figure 8**, there may be a high correlation between the predictor variables *Age* and *Years of Education* that might create multicollinearity. Often this multicollinearity makes each predictor appear to be not significantly associated with the dependent variable when one or both actually are.

Figure 8 Multicollinearity between *Age* and *Years of Education*

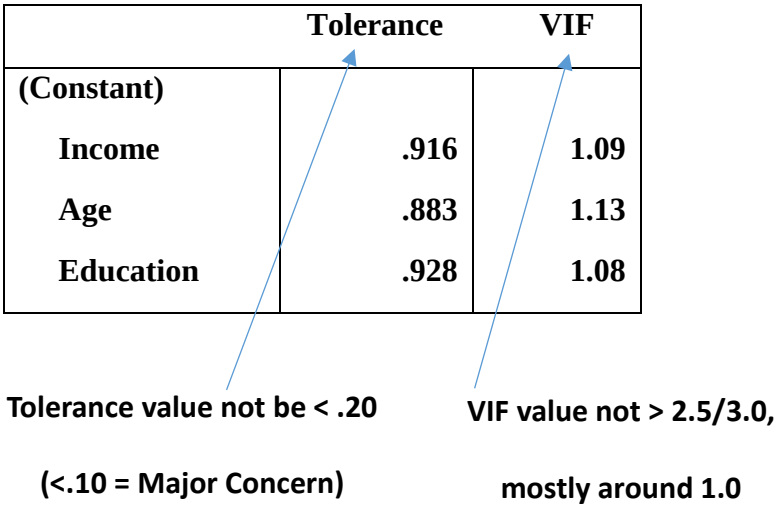


The assumption of multicollinearity may be examined through a simple function in the linear regression function in SPSS, where you would go to:

- In SPSS go to: *Analyze*, *Regression*, *Linear*
- Enter *dep. variable* e.g., *differenceprepost*
- Enter *Ind. variable(s),* e.g., *income level, etc.*
- Click *Statistics*, click *collinearity stats*, *Continue*
- Click *OK* or *PASTE* (if *Paste* then run)

.

Figure 9. Tolerance and VIF in SPSS output



We have completed our review of **Check 2: Test Assumptions**. Now, we will make a brief review of **Check 4: Measurement Tools** to conclude our review of **Step 3: Checks of Data Integrity** for out Pretest/Posttest study.

Check 1: Statistical Power (Done in week 1!)

Check 2: Test Assumptions (Done week 2!)

Check 3: Missing Data (week 4)

Check 4: Measurement Tools (week 2)

Check 4: Measurement Tools

The study measurement tools play a significant role in determining if data are appropriate for analysis. Typically, any aspects of **reliability** and **validity** associated with each tool are assessed, many times prior to data analysis. Perhaps the most common assessment of a measurement tool done after data collection is assessing **internal consistency** reliability, which is most often expressed using the Cronbach's alpha.

An instrument is said to be internally consistent to the degree that all scale items measure the same trait or construct. For example, regarding our measure of the dependent variable *Happiness* (Pre/Post), the scale would be internally consistent if all the five items used to compute the total *Happiness* score were measuring the same construct (at least at an acceptable level). When a set of items are measuring one construct the items will be correlated in a pattern.

For example, view the five items below in **Figure 10**, which measure the dependent variable *Happiness*, in SPSS. We see a pattern reflecting the highest level of happiness. Specifically, when the participant selects a 5 (Strongly Agree) for the positively stated items (Happy, Good, Strong, Glad) but a 1 (Strongly Disagree) for the negatively stated item (sad). The Cronbach's alpha is a quantitative measure of these patterns.

Figure 10 The pattern of responses indicating the highest level of *Happiness*

In the last 7 days I been:					
	Strongly Disagree	**Disagree**	**Neither Agree or Disagree**	**Agree**	**Strongly Agree**
Happy	1	2	3	4	5
Sad	1	2	3	4	5
Good	1	2	3	4	5
Strong	1	2	3	4	5
Glad	1	2	3	4	5

You can produce the Cronbach's alpha in SPSS for a set of scale items by going to:

- *Analyze, Scale, Reliability Analysis*
- Transfer all items in the scale into the right hand column, Click *Statistics*
- Click *Scale if item deleted* (to see if some items contribute to a lower score), click *Continue*
- Click *OK* or *PASTE* (if *Paste* then run)

Figure 11. SPSS Output for a Reliability Analysis

Reliability

Reliability Statistics

Cronbach's Alpha	N of Items
.887	5

A Cronbach's alpha of .70 or above indicates an acceptable level of internal consistency

We have completed our review of **Check 2: Test Assumptions** and **Check 4: Measurement Tools** to conclude our review of **Step 3: Checks of Data Integrity**.

Check 1: Statistical Power (Done in week 1!)

Check 2: Test Assumptions (Done week 2!)

Check 3: Missing Data (week 4)

Check 4: Measurement Tools (Done week 2!)

Step 4: Univariate Analysis

What we are asking:
What are the characteristics of each individual study variable?

Univariate analysis, also known as **descriptive analysis** presents the characteristics of each variable individually. Usually these characteristics are examined via the statistical procedure known as the *Frequencies analysis* (as presented in **Figure 12. The Univariate Test Key**). As presented in **Figure 13. Univariate Test Key (Study Variables Plugged In)**, the characteristics of continuous variables (e.g., Education Level, Study Group) are typically reported as the mean, standard deviation, and minimum/maximum scores. Categorical variables (e.g., Income Level, Happiness Difference Scores) are usually presented as the number and percentage of study participants within each category.

Figure 12 Univariate Test Key

Variable	Test to Use (Values to Report)
Categorical	Frequencies (Number & Percentage)
Continuous	Frequencies (Mean, Std. Deviation, Min/Max)

Figure 13 Univariate Test Key (Study Variables Plugged In)

Variable	Test to Use (Values to Report)
Categorical	Frequencies (Number & Percentage)
Education Level	Frequencies (Number & Percentage)
Study Group	Frequencies (Number & Percentage)
Continuous	Frequencies (Mean, Std. Deviation, Min/Max)
Income Level	Frequencies (Mean, Std. Deviation, Min/Max)
Happiness Difference Scores	Frequencies (Mean, Std. Deviation, Min/Max)

To perform a frequencies analysis in SPSS go to:

- *Analyze*, *Descriptive Statistics, Frequencies*
- Enter all *variables* e.g., *differenceprepost, etc.*, into the right hand-column
- Under *Statistics* check *mean, standard dev., MIN/MAX* then *Continue*
- Click *OK* or *PASTE* (if *Paste* then run)

Figure 14 presents the statistical output for the frequencies procedure addressing the categorical study variables. The first box labeled **Statistics** reports the number of cases with valid and missing values, which indicates 100 valid cases and 0 missing for each variable, which means both variables have full data and no missing data points. The next box (labeled **Frequency Table**) presents the frequency counts reflecting how many study participants are in each category within each variable. For example, regarding the variable *Education Level*, among the 100 study participants, 24 (24%) are at the High School/GED level, 38 (38%) are at the College level, and 38 (38%) are at the Graduate school level. Regarding the variable *Study Group* of the 100 study participants, 50 (50%) are in the experimental group and 50 (50%) are in the control group.

Figure 14

Frequencies

Statistics

		Education Level	Study Group
N	Valid	100	100.0
	Missing	0	0

Frequency Table

Education Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High School/GED	24	24.0	24.0	24.0
	College	38	38.0	38.0	62.0
	Graduate School	38	38.0	38.0	100.0
	Total	100	100.0	100.0	

Study Group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Experimental	50	50.0	47.0	47.0
	Control	50	50.0	53.0	100.0
	Total	100	100.0	100.0	

Figure 15 presents the statistical output for this frequency procedure addressing continuous study variables. The first box (labeled **Statistics**) in the output reports the number of cases with valid and missing values. Again, this box indicates that for both variables there are complete data for all 100 study participants. That same box presents the values for *Income Level* reflecting the mean of $39,680 (*SD*=15.53) and a minimum/maximum score of $21,000 and $75,000, respectively. The data also described the average (Mean) *Happiness Difference Score* is .18 (*SD*=.25) with a minimum/maximum score of -.20 and .80, respectively.

Figure 15

Frequencies

Statistics

		Income Level	Happiness Difference Scores
N	Valid	100	100
	Missing	0	0
Mean		39.68	.18
Std. Deviation		15.53	.25
Minimum		21.0	-.20
Maximum		75.0	.80

.

Step 5: Bivariate Analysis

Which predictor variables (Education Level, Income Level, & Study Group) are significantly associated with Pre/Post Change Scores?

Significant predictors are included in Step 6: Multivariate Analysis

Bivariate Analysis involves looking at how two variables at a time relate to one another, such as comparing each predictor variable with the dependent variable. Keep in mind, we want to include all study variables related to the dependent variable at a statistically significant level ($p<.05$) at the bivariate level in the multivariate regression model/Repeated Measures GLM. Therefore, a primary goal of bivariate analysis is not just to test the association between two variables, but also identify which study variables are related to the dependent variable, so they may be included as predictors in the final multivariate regression model conducted in **Step 6: Multivariate Analysis**.

Figure 16 presents the *Bivariate Test Key*, which describes the appropriate statistical procedure to test the association between two variables, will depend on the structure of each variable. **Figure 17** presents the *Bivariate Test Key* with the study variables plugged in. The first line instructs if Variable 1 is categorical with a two category response, such as *Study Group* and Variable 2 is continuous, such as *Happiness Difference Scores* an **Independent Samples T-Test** would be the appropriate. The second line describes that if Variable 1 is categorical with three or more categories, such as *Education Level* and Variable 2 is continuous, such as *Happiness Difference Scores* a **One-Way ANOVA** would be the appropriate. The third line instructs if Variable 1 is continuous, such as *Income Level* and Variable 2 is continuous, such as *Happiness Difference Scores* a **Correlation** would be the appropriate. Lastly, a chi square analysis is appropriate when each variable is categorical.

Figure 16 Bivariate Test Key

Variable 1	Variable 2	Test To Use
Categorical (2 categories)	Continuous	Independent Samples T-Test
Categorical (≥3 categories)	Continuous	One-Way ANOVA
Continuous	Continuous	Correlation
Categorical	Categorical	Chi-Square

Figure 17 Bivariate Test Key (Study Variables Plugged In)

Variable 1	Variable 2	Test To Use
Categorical (2 categories)	Continuous	Independent Samples T-Test
Study Group (Experim., Control)	Hap. Change (-4-4)	Independent Samples T-Test
Categorical (≥3 categories)	Continuous	One-Way ANOVA
Education (HS/G, C, GS)	Hap. Change (-4-4)	One-Way ANOVA
Continuous	Continuous	Correlation
Income (Min-Max)	Hap. Change (-4-4)	Correlation
Categorical	Categorical	Chi-Square

One-Way ANOVA

The Bivariate Test Key indicates a **One-Way ANOVA (Analysis of Variance)** is the appropriate statistical procedure examining the relationship between a categorical variable with three or more response categories with a continuous variable, such as the categorical covariate variable *Education Level* with the continuous dependent variable *Happiness Difference Scores*. This procedure will indicate if there is a statistically significant difference in mean *Happiness Difference Scores* among study participants with a High School/GED, College, or Graduate School level of education. To conduct the One-Way ANOVA in SPSS go to:

- *Analyze, Compare Means, One-Way ANOVA*
- In *Factor Var.* enter *Education Level (Cat. var.)*
- In *Dependent List*, enter *Pre/Post Change Score (Cont. var.)*
- Under *Post-Hoc*, click *Bonferroni, Continue*
- Under *Options*, click *Descriptive, Continue*
- *Click OK or PASTE (if Paste then run)*

.

Figure 18

Oneway

(2nd) Directionality:

Higher education level = Higher *Happiness Change Scores*

Descriptives

Happiness

	N	Mean	SD	SE	95% CI for the Mean		Min	Max
					Lower	Upper		
High School/GED	24	.01	.16	.03	-.05	.08	-.2	.4
College	38	.18	.22	.03	.10	.25	-.1	.6
Graduate School	38	.28	.26	.04	.20	.37	-.1	.8
Total	100	.18	.25	.02	.13	.23	-.2	.8

ANOVA

(1st) Significance (Overall Model):

Statistically significant (p<.05)

Happiness

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.09	2	.54	10.83	.000
Within Groups	4.86	97	.05		
Total	5.95	99			

Post Hoc Tests

(1st) Significance (Mean Scores):

Statistically significant (p<.05)

(Mean score differences)

Multiple Comparisons

Dependent Variable: Happiness

Bonferroni

(I) Education Level	(J) Education Level	Mean Difference (I-J)	Std. Error	Sig.	95% CI for the Mean	
					Lower	Upper
High School/GED	College	-.16*	.06	.017	-.31	-.02
	Graduate School	-.27*	.06	.000	-.41	-.13
College	High School/GED	.16*	.06	.017	.02	.31
	Graduate School	-.11*	.05	.123	-.23	-.02
Graduate School	High School/GED	.27*	.06	.000	.13	.41
	College	.11*	.05	.123	-.02	.23

*The mean difference is significant at the 0.05 level.

The data in **Figure 18** indicates a statistically significant relationship between variables as the probability level for this test was less than .05 ($p<.05$) for the overall test, as well as in the post hoc tests where individual means are compared. In terms of directionality, the mean scores, as well as the post hoc test indicated that a higher *Education Level,* was associated with a higher level of *Happiness Difference Scores,* relative to a lower Education Level.

Correlation

The Bivariate Test Key indicates a correlation is the appropriate statistical procedure examining the relationship between a continuous variable with another continuous variable. Therefore, we will use this procedure to examine the relationship between the continuous covariate variable *Income Level* with the continuous dependent variable *Happiness Difference Scores*. To conduct the Pearson's correlation in SPSS go to:

- *Analyze, Correlate, Bivariate*
- Enter Continuous Variables (e.g., Income Level, Happiness Difference Scores) in Right Hand Column titled *Variables*
- Click *OK* or *PASTE* (if *Paste* then run)

Figure 19 presents the statistical output for the **Pearson's correlation** procedure. Overall, the Pearson's correlation indicated a statistically significant relationship between variables as the probability level for this test was less than .05 ($p<.05$), where *Happiness Difference Scores* increase as *Income Level* increases.

Figure 19

Correlations

(2nd) Directionality:
Positive relationship (no -)

Correlations

		Income Level	Happiness Difference Scores
Income Level	Pearson Correlation	1	.884**
	Sig. (2-tailed)		.000
	N	100	100
Happ-iness Dif Sc	Pearson Correlation	.884**	1
	Sig. (2-tailed)	.000	
	N	100	100

(1st) Significance:
Statistically significant

**Significant at the 0.01 level (2-tailed).

Independent-Samples T-Test

The bivariate test key indicates the **independent-samples t-test** is the appropriate statistical procedure to use when examining a continuous variable with a categorical predictor with two response categories, such as the categorical independent variable *Study Group* with the continuous dependent variable *Happiness Difference Scores*. Data in **Figure 20** indicate a statistically significant relationship where the experimental group evidenced significantly higher pretest to posttest *Happiness Difference Scores.*

Figure 20

(2nd) Directionality:
Experimental Group =
Higher *Happiness Difference Scores*

(1st) Significance:
Statistically
Significant (*p*<.05)

T-Test

Group Statistics

	Study Group	N	Mean	Standard Deviation	Std. Error Mean
Happiness Difference S	Experimental	50	.3560	.2226	.0315
	Control	50	.0012	.0872	.0123

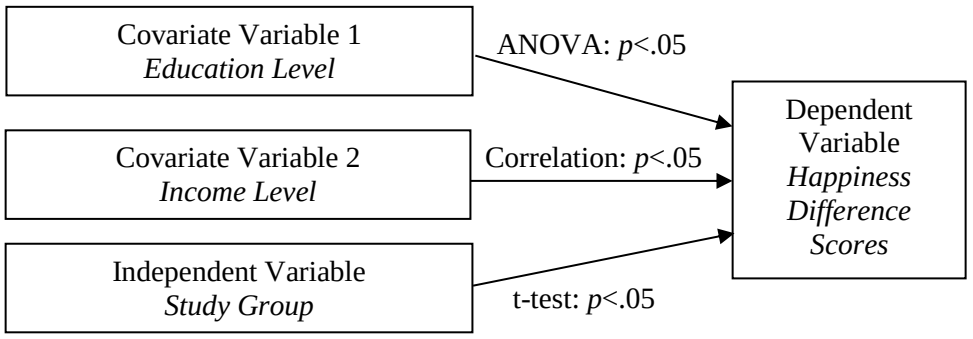
Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means					
		F	Sig	t	df	Sig. (2-tail)	Mean Diff.	95% CI of the Difference	
								Low	Up
Happiness Diff Sc	Equal Variances assumed	34.	.00	11.	98	.000	.35	.29	.42
	Equal Variances not assumed			11.	69.3	.000	.35	.29	.42

What Did Bivariate Analysis Tell Us?

Figure 21 reflects the results on the three bivariate tests used in sample study 1a. Notice that we have entered an arrow connecting each predictor variable with the dependent variable that lists the test used and resulting level of statistical significance. In summary, each bivariate relationship evidenced a statistically significant relationship. Therefore, each predictor will be included in **Step 6: Multivariate Analysis**.

Figure 21 What Bivariate Analysis Tells Us for Sample Study 1a?



Step 6: Multivariate Analysis

What we are asking:

While controlling for significant covariate variables (Education Level & Income Level), is the independent variable (Study Group) significantly associated with Pre/Post Happiness Change Scores?

Consider the use of MLR & Repeated Measures GLM

In this step we will employ multivariate analysis to identify which predictor variable (*Education Level*, *Income Level*, *Study Group*) is the strongest predictor of the dependent variable *Happiness Difference Scores*, which was the overall goal of our data analysis study. **The Multivariate Test Key** presented in **Figure 22** describes that selecting the appropriate multivariate statistical procedure depends upon the structure (i.e., categorical or continuous) of the dependent variable. **Figure 23** presents the **Multivariate Test Key with the study variable plugged in**, which instructs that the appropriate regression model to use when examining a continuous dependent variable, such as *Happiness Difference Scores* is a multiple linear regression. **When linear regression involves more than one predictor, the procedure is termed *multiple linear regression*, which is the term we use for this procedure**.

Figure 22 The Multivariate Test Key

Dependent Variable	Regression to Use
Categorical (≥3 categories)	Multinomial Logistic (Not Presented here)
Categorical (2 categories)	Binary Logistic
Continuous	Linear

Figure 23 Multivariate Test Key with the study variable plugged in

Dependent Variable	Regression to Use
Categorical (≥3 categories)	Multinomial Logistic (Not Presented here)
Categorical (2 categories)	Binary Logistic
Continuous	Linear *(>1 Predictor = Multiple Linear)*
Continuous (-4-4)	Happiness Difference Scores (-4-4)

Dummy-Coding Variables

Dummy-Coding is the key to using a categorical variable with three or more response categories in a regression model. Before the analysis is performed, an important consideration must be made if a categorical predictor variable with three or more response categories is to be included in the regression model. Specifically, if such a categorical variable will be used in the regression model, each response category within the original categorical predictor variable must be **dummy-coded** into a separate **Yes** or **No** dichotomous categorical variable.

For example, in the regression model for sample study one, the categorical predictor variable *Education Level* will be included, which has three response categories (High School/GED, College, and Graduate School). To use the variable *Education Level* in the regression model, each response category must be made into a separate Yes or No dichotomous categorical variable, which we will describe below. First, consider the original single variable *Education Level* along with the three response categories (note in SPSS data base response categories are called *Values*). Recall, when we entered these data into the SPSS database, we ascribed the categories the numbers 1, 2, and 3, as presented below:

Response Category (Value) 1: High School/GED (Coded as "1" in SPSS)
Response Category (Value) 2: College (Coded as "2" in SPSS)
Response Category (Value) 3: Graduate School (Coded as "3" in SPSS)

When we dummy-code the variable *Education Level*, we create **three new Yes/No variables** to use in the regression model in place of the original single variable.

Conducting Multiple Linear Regression Analysis

To conduct the multiple linear regression analysis procedure in SPSS go to:

- In SPSS: *Analyze*, *Regression, Linear*
- Put DV in *Dependent* Box
- Put CV(s) & IV(s) in *Independent(s)* Box
- Remember *Collinearity Stats*, *ZPRED/ZRESID*
- Click *OK* or *PASTE* (if *Paste* then run)

Interpreting the Statistical Output: Multiple Linear Regression Analysis. **Figure 23** presents the statistical output for the **Multiple Linear Regression Analysis** procedure. In this section we use this statistical output to identify the three dimensions of the relationship between the dependent variable *Happiness Difference Scores* and predictor variables (covariate and independent variables) in the context of the full model. Specifically, we will present the relationship dimensions of significance, directionality, and magnitude in three separate parts (Part A, Part B, and Part C, respectively).

Part A Relationship Dimension 1: Significance

Overall Model. Note the second box in the output labeled **ANOVA**. In the final column labeled **Sig.**, the level of probability (statistical significance) for the overall test is indicated, which is **.000**. Thus, the overall model for the **multiple linear regression model** procedure is statistically significant ($p<.05$). Therefore, we will continue to examine the results of the test.

Individual Predictor Variables. Next, refer to the final table labeled **Coefficients**. This table provides information regarding the relationship between each predictor variable with the dependent variable. First, refer to the final column labeled **Sig.**, which presents the probability levels for these relationships. We see that all values are below .05 ($p<.05$), which indicates that all the predictor variables have a statistically significant

relationship with the dependent variable. If a value greater that .05 (p>.05) we would not consider the relationship between that predictor and the dependent variable.

Part B Relationship Dimension 2: Directionality

The Unstandardized Beta (regression coefficient). Within the **Figure 23**, refer to the final table labeled **Coefficients**. Refer to the first column under the label Unstandardized Coefficients labeled **B**, which indicates the directionality of the relationships between the predictor variables with the dependent variable. Specifically, this column presents the Unstandardized Beta. For example, observe the two dummy-coded variables at the top of the first column, *Education Level: College* and *Education Level Graduate School*. Notice that the unstandardized beta for each of these variables does not begin with a minus sign (.07 and .10) indicating a positive relationship. However, recall there is a Reference group (*Education Level: High School/GED*) for these groups.

Therefore, the positive betas, along with the values reflecting statistical significance (p<.05 as Sig. = .000 and .000), indicate that study participants with a level of education at the *College* and *Graduate School* levels have significantly higher scores (recall positive relationship indicates higher scores) reflecting *Happiness Difference Scores* **in reference to** study participants with a *High School/GED* level of education.

Next, refer to covariate predictor variable *Income Level*. Again, we see under the Unstandardized Coefficients column, that the value for the beta (**B**) is positive (0.008) as there is not a minus sign, indicating a positive association. Specifically, this positive unstandardized beta indicates that as the covariate predictor variable *Income Level* increases, the dependent variable *Happiness Difference Scores* also increase.

Lastly, notice that the beta (**B**) for the independent variable *Study Group* is also positive as there is not a minus sign in front of the unstandardized beta. In order to interpret the meaning of the unstandardized beta here, recall that experimental group is coded as 1 and Control Group is coded as 2 in the SPSS database. Thus, the positive beta suggests as the predictor *Study Group* increases from 0 to 1, or in conceptual terms from *Experimental Group* to *Control Group*, *Happiness Difference Scores* go up.

Figure 23

Regression

(3rd) Magnitude:
Large R^2 effect size

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.909	.827	.820	.1040

(1st) Significance (model):
Statistically significant (p<.05)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.92	4	1.23	.01	.000
	Residual	1.03	95	.229		
	Total	5.95	99			

(1st) Significance (predictors):
Statistically significant (p<.05)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta (β)		
1	(Constant)	-.374	.035		-10.6	.000
	Education Level: College	.074	.029	.147	2.5	.014
	Education Level: Graduate School	.100	.035	.199	2.9	.005
	Income Level	.008	.001	.436	8.0	.000
	Study Group	.346	.021	.710	16.6	.000

(2nd) Directionality:
Unstandardized Beta (B) indicates all positive relationships

(3rd) Magnitude:
Standardized Beta (β) indicates the strongest predictor

Part C Relationship Dimension 3: Magnitude

However, the linear regression analysis procedure in SPSS does not have an option to estimate the effect size between variables. However, an equivalent procedure will produce the effect size estimate of the partial Eta squared statistic through the ANCOVA (Analysis of Covariance) statistical procedure in SPSS by going to:

- In SPSS: *Analyze, General Linear Model, Univariate*
- Put DV in *Dependent Variable* Box
- Put CV(s) in *Covariate(s)* Box
- Put IV (categorical IV) in *Fixed Factor(s)* box
- *Options* = Descriptives & Est. Effect Size
- Click *OK* or *PASTE* (if *Paste* then run)

Figure 24 presents the results of the ANCOVA, which indicates that the independent variable Study Group evidenced the largest effect size of .742, which is a very large effect size.

Figure 24

Tests of Between-Subjects Effects

Dependent Variable: Happiness

Source	Type III Sum of Squares	df	Mean Sqr	F	Sig.	Partial Eta Squared
Corrected Model	4.906	3	1.64	150.76	.000	.825
Intercept	.508	1	.51	46.79	.000	.328
Income	.963	1	.69	63.92	.000	.400
Education	.082	1	.08	7.57	.007	.073
studygroup	2.989	1	2.99	274.54	.000	.742
Error	1.041	96	.01			
Total	9.138	100				
Corrected Total	5.948	99				

(3rd) Magnitude:

IV: Medium to Large effect size (PES = .74)

What Did Multivariate Analysis Tell Us?

Results on the multiple linear regression analysis used in sample study 1a examining which predictor variable is the strongest predictor of the dependent variable *Happiness Difference Scores*. We saw that at the multivariate level, all predictors evidenced a statistically significant relationship ($p<.05$) with the dependent variable. After the effects of both covariate predictor variables *Education Level* and *Income Level* were controlled for in the multivariate model, the independent variable *Study Group* was related to the dependent variable *Happiness Difference Scores* at a statistically significant level where the *Experimental Group* evidenced significantly higher changes. An ANCOVA procedure also indicated that Study Group also evidenced the largest effect upon the dependent variable with a very large PES effect size.

Repeated Measures GLM

In addition to a MLR, pretest posttest data analysis might also employ **Repeated Measures GLM** as in multivariate analysis. A **Repeated Measures GLM** can be performed in SPSS by going to:

- *Analyze, General Linear Model, Repeated Measures*
- Enter a variable name in the *Within Subject Factor Name box*, e.g., *PrePostChange (no space)*
- In *Within Subjects Var.*, enter *Pretest, Posttest*
- In *Between Subjects Factor(s)*, enter *Study Group*
- In *Covariate(s)* box, enter *Education & Income Level*
- *Options = Descriptives, Effect Size, Obs. Power*
- Click *OK* or *PASTE* (if *Paste* then run)

Figure 25 presents the **Descriptives Table** for the **Repeated Measures GLM** multivariate analysis. It is clear at pretest, the mean Happiness scores for the Experimental and Control group were alike (2.54 vs. 2.54). However, at posttest while the mean score for the Control group remained the same (2.54), the Experimental group increased to a mean score of 2.90.

Figure 25

Descriptives table for the Repeated Measures GLM

Study Group		Mean	Standard Deviation	N
Pretest Happiness Scores	Control	2.54	.64	50
	Experimental	2.54	.66	50
Total		2.54	.65	100
Posttest Happiness Scores	Control	2.54	.62	50
	Experimental	**2.90**	.57	50
Total		2.72	.62	100

Figure 26 presents the **Statistical Findings of Repeated Measures GLM** multivariate analysis. We see that the findings here mirror the findings of the MLR, where all the predictors are significantly related to pretest to posttest changes in happiness scores, as well as the independent *Study Group* evidences the strangest and considerably large PES effect size upon the outcome variable.

Figure 26

The main change in scores = Experimental group at Posttest

Statistical Findings of Repeated Measures GLM

Effect	F	Sig.	Partial Eta Squared	Observed Power
PrePostChange	46.8	.000	.33	1.00
PrePostChange*Income	63.9	.000	.40	1.00
PrePostChange*Education	7.6	.007	.07	.78
PrePostChange*Studygroup	275.5	.000	.74	1.00

All Statistically Significant

Study Group has the largest PES

Sufficient power (.80) for each predictor