# The Ideal Qualitative Study with a Quantitative Component
# 6 Week Webinar Class

## CLASS 5:

## STATISTICAL ANALYSIS WITH SMALL SAMPLES

Welcome to week five of our 6 week webinar class *The Ideal Qualitative Study with a Quantitative Component*. The focus of this week is completing the quantitative analysis section of our study titled *Essentials of Mixed Methods Research*.

**Week 1:** Intro. & Quantitative Analysis Part 1

**Week 2:** Quantitative Analysis Part 2

**Week 3:** Essentials of Qualitative Analysis

**Week 4:** Essentials of Mixed Methods Research

**Week 5:** Statistical Analysis with Small Samples

**Week 6:** Write-up and Report

### Introduction

Recall, parametric and nonparametric tests are two broad classifications of statistical procedures. Parametric tests involve test assumptions that may be difficult to satisfy when using small sample size. In these instances, nonparametric tests are commonly used as alternatives.

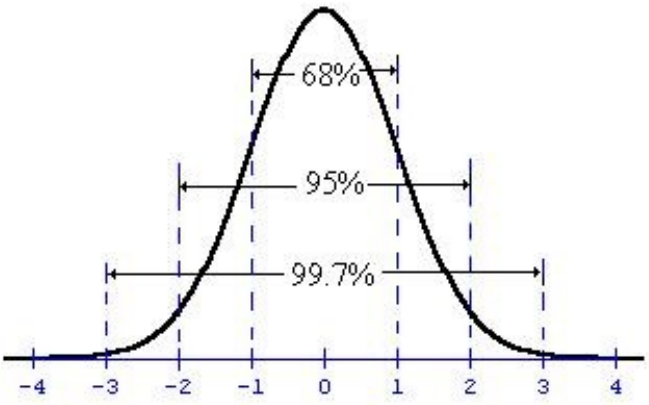
Specifically, parametric tests are based on assumptions regarding the underlying population from which the sample was drawn. For example, parametric tests assume scores are approximately normally distributed *within a population*. Therefore, *within our sample*, variable scores should be normally distributed (e.g., age, class enjoyment, class attendance) to reflect the population. It is often difficult for a small number of study participants (e.g., $n$ <30) to reflect the population characteristics.

But don't take my word for it! Let's compare normality of the distribution of scores among the 100 community residents relative to the distribution of scores of a random selection of 25 residents from that same group. Keep in mind, parametric tests have several test assumptions to consider and a normal distribution is just one of them. However, we will use the examination of a normal distribution to illustrate our point in this example.

First, let's review the factors that impact normality. Figure 1 presents the classic bell shaped curve associated with a normal distribution of scores. The 0 in the center of the bottom line reflects the mean score for the distribution. The -4 through 4 on the bottom line reflects the standard deviations, which describe how the cases are spread out from the mean score. Notice within the normal distribution, approximately two thirds (68%) of the scores are in center of the distribution within one standard deviation of the mean score. The considerably higher and lower scores within the distribution fall to the left and right outside the one standard deviation mark and are fewer in number.

**Figure 1**

**The Classic Bell Shaped Normal Distribution of Scores**



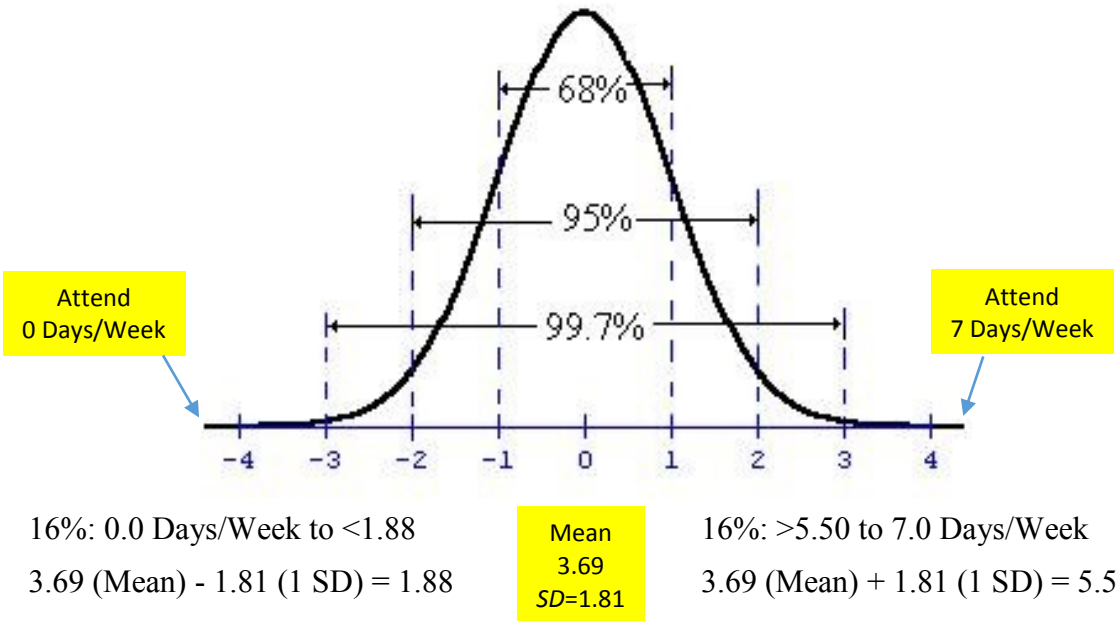

To better illustrate the normal distribution, **Figure 2** presents the distribution of scores regarding the dependent variable *Class Attendance* for the full 100 community residents involved in our mixed methods study. We see in the center of the bottom line, the mean value within the distribution is 3.69 and the standard deviation is 1.81.

If we subtract 1 SD (1.81) from the 3.69 mean score the value 1.88 is produced, which will reflect the value 1 SD below the mean score. If we add 1 SD (1.81) to the 3.69 mean score the value 5.50 is produced, which will reflect 1 SD above the mean score. Therefore, based upon these numbers, we would say that 68% of residents attend class between 1.88 and 5.50 days/week (i.e., 1 SD above and below the mean score of the distribution).

After accounting for this 68% of scores in the distribution, there is still another 32% to examine (68% + 32% = 100% of scores in the distribution), which reflect the considerably lower and higher *Class Attendance* scores. The considerably lower *Class Attendance* scores would fall to the left (the 17% of scores considerably lower than the mean score) and right (the 17% of scores considerably higher than the mean score) of the -1 SD and 1 SD marks.

**Figure 2**

**Distribution of Scores for Class Attendance (*N*=100)**




68% of residents attend class between 1.88 and 5.50 days/week

## Assessing Normality within a Distribution

Normality will be impacted by the skewness and kurtosis of the distribution. The skewness of the peak examines if the peak is in the center of the distribution. Kurtosis addresses if cases are appropriately distributed into the tails of the distribution. **Figure 3** illustrates poor skewness where the peak favors the left or right of the distribution. **Figure 4** presents poor kurtosis where there are too many cases in the tails (distribution *B*), too few cases in the tails (distribution *C*), as well as normal kurtosis (distribution *A*), where there is an appropriate number of cases in the tails.

**Figure 3**

**Poor Skewness Where The Peak Favors the Left or Right**

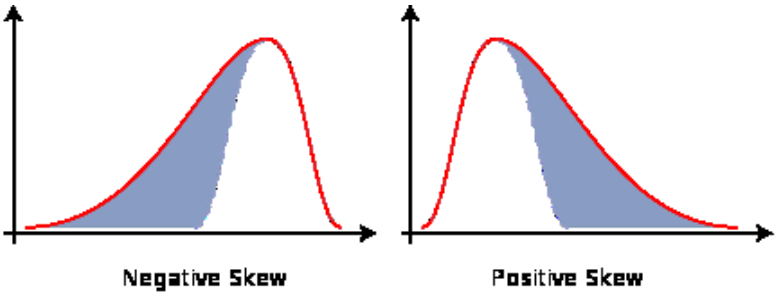
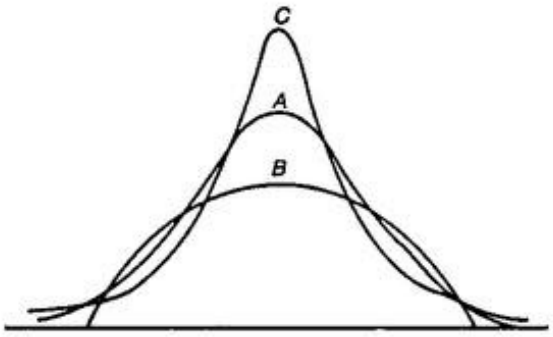



**Figure 4**

**Kurtosis (how cases are dispersed into the tails)**



## Assessing if a Distribution is Normal

We can assess if a distribution of scores is normal through examining if the value of the skewness is within 3 times the standard error of the skewness, as well as if the value of the kurtosis is within 3 times the standard error of the kurtosis. In order to produce these values in SPSS go to:

1) Analyze >Descriptive Statistics >Frequencies >Enter var., e.g., *Class Attendance*

2) Under *Statistics*, check Skewness & Kurtosis, Continue, OK or Paste

**SPSS Output 1** presents the values for the skewness and kurtosis (and the respective standard error of each) regarding the continuous variables included in our study among the full 100 community residents involved with this research.

**SPSS Output 1**

**Examining Normality: 100 Residents**

**Statistics**

| | | Age | Class Enjoyment | Class Attendance |
|---|---|---|---|---|
| N | Valid | 100 | 100 | 100 |
| | Missing | 0 | 0 | 0 |
| Skewness | | -.35 | .01 | -.05 |
| Std. Error of Skewness | | .24 | .24 | .24 |
| Kurtosis | | -1.11 | -1.32 | -.84 |
| Std. Error of Kurtosis | | .48 | .48 | .48 |

**The Skewness/Std. Error of Skewness & Kurtosis/Std. Error of Kurtosis Ratios**

**Figure 5** presents the ratio of the skewness relative to the standard error of the skewness (Skewness/Std. Error of the Skewness), as well as the ratio to the kurtosis relative to the standard error of the kurtosis (Kurtosis/Std. Error of the Kurtosis) among the full sample of 100 residents. We see that when each value is divided by the respective standard error, a ratio is produced that conveys the size of the value relative to the standard error. Here we see that the ratio of each value to the standard error is below 3, which reflects the distribution of each is approximately normal among the 100 community residents involved in the mixed methods study.

**Figure 5**

**The Skewness/Std. Error of Skewness & Kurtosis/Std. Error of Kurtosis Ratios for the Full Sample of 100 Residents**

| | **Age** | **Class Enjoyment** | **Class Attendance** |
|---|---|---|---|
| Skewness/SE Skewness | -.35/.24 = | .01/.24 = | -.05/.24 = |
| **Ratios:** | **1.46** | **.04** | **.21** |
| Kurtosis/SE Kurtosis | -1.11/.48 = | -1.32/.48 = | -.84/.48 = |
| **Ratios:** | **2.31** | **2.75** | **1.75** |

**SPSS Output 2** presents the values for the skewness and kurtosis (and the respective standard error of each) regarding the continuous variables included in our study among the 25 community residents comprising the small sample involved with our research.

**The Skewness/Std. Error of Skewness & Kurtosis/Std. Error of Kurtosis Ratios**

**Figure 6** presents the ratio of the skewness relative to the standard error of the skewness (Skewness/Std. Error of the Skewness), as well as the ratio of the kurtosis relative to the standard error of the kurtosis (Kurtosis/Std. Error of the Kurtosis) for the partial sample of 25 residents. Again, we see that when each value is divided by the respective standard error, a ratio is produced that conveys the size of the value relative to the standard error. Here we see of the six ratios, two are well above 3, which reflects two of the distributions are not approximately normal. Specifically, the skewness and kurtosis (4.78 and 4.02, respectively) of the continuous **Covariate Variable** *Class Enjoyment* are now non-normal.

**SPSS Output 2**

**Examining Normality: 25 Residents**

**Statistics**

| | | Age | Class Enjoyment | Class Attendance |
|---|---|---|---|---|
| N | Valid | 25 | 25 | 25 |
| | Missing | 0 | 0 | 0 |
| Skewness | | -1.33 | 2.20 | .00 |
| Std. Error of Skewness | | .46 | .46 | .46 |
| Kurtosis | | .83 | 3.62 | -1.50 |
| Std. Error of Kurtosis | | .90 | .90 | .90 |

**Figure 6**

**The Skewness/Std. Error of Skewness & Kurtosis/Std. Error of Kurtosis Ratios for the Partial Sample of 25 Residents**

| | **Age** | **Class Enjoyment** | **Class Attendance** |
|---|---|---|---|
| Skewness/SE Skewness | -1.33/.46 = | 2.20/.46 = | .00/.46 = |
| **Ratios:** | **2.89** | **4.78** | **.00** |
| Kurtosis/SE Kurtosis | .83/.90 = | 3.62/.90 = | -1.50/.90 = |
| **Ratios:** | **.92** | **4.02** | **1.67** |

Thus, through comparing the ratios in **Figures 5** and **6**, we can see that even among the same sample of study participants, when the size of the sample is reduced, it is more difficult to meet parametric tests assumptions such as an approximately normal distribution of scores.

It is important to keep in mind that incorrect results and conclusions result when data deviate strongly from the assumptions of a parametric procedure. Therefore, at times it is necessary to identify alternatives to parametric tests when these assumptions are not met.

## Nonparametric Tests

The use of the nonparametric equivalents of parametric tests has been the popular solution for performing data analysis when data do not meet parametric test assumptions. Nonparametric tests are not based upon as many assumptions (e.g., shape/parameters of the population distribution) as parametric procedures. There are several analogous nonparametric procedures that can be employed in place of parametric tests.

However, it is important to consider that nonparametric tests are not absolute and complete substitutes for parametric testing. Specifically, nonparametric testing incorporates significant limitations that must be addressed and often accounted for in order to produce a sound research study.

## The Limitations of Nonparametric Tests

Nonparametric tests generally have less statistical power using the same sample size relative to parametric procedures. Therefore, analysis is less likely to show a significant variable relationship even when the relationship exists within data. For example, the CV *Class enjoyment* may predict DV *Class Attendance*. However, if statistical power is an issue due to a limited sample size, a nonparametric test may indicate the relationship is not significant, where the parametric test would identify this significant association.

Furthermore, nonparametric tests are limited in describing the variable relationships. For example, as intimated in **Table 1**, nonparametric tests may produce the equivalent of our parametric bivariate analysis. However, nonparametric tests cannot accommodate a multivariate analysis. Therefore, data interpretation is difficult as the relative strength (which is the strongest predictor?) of predictors in explaining the DV can't be assessed. Subsequently, many times, it may be worth conducting both the parametric and nonparametric *versions* of the same test.

Specifically, *nonparametric tests* may act as a complement to parametric tests toward helping to validate the methods and findings when parametric test assumptions are violated. In essence, just because you have a small sample, it does not mean that you can only use nonparametric testing.

One important point in this line of reasoning is that parametric tests are said to be *robust*. Statistical *robustness* suggests findings of parametric tests are accurate even when assumptions (e.g., normality) are violated. Therefore, if parametric and nonparametric tests equivalents yield similar results (e.g., the same statistically significant relationships are indicated), it could be suggested parametric tests are performing in a robust manner as *findings are similar in the nonparametric test where there are not such assumptions, as well as the parametric test where the assumptions are not met/violated*.

Thus, consider using *nonparametric tests* as a complement to the *parametric tests* in a study using a small sample. The combination of *Nonparametric & parametric* tests may be a fuller/more descriptive method relative to nonparametric tests only.

In such analyses, limitations are noted and many times findings are called *preliminary*, a.k.a., *I'm not saying, I'm just saying*. In other words, we are not suggesting findings are true for the population or should guide policy or practice changes. We are instead saying these valuable findings are what the data indicated and may warrant further study.

## Analogous Parametric & Non-Parametric Tests

**Table 1** presents the bivariate parametric statistical tests we used in quantitative analysis, along with the analogous non-parametric equivalent of each test. The table describes the related parametric and nonparametric test to be used according to the goal of each analysis. We will next apply each of these statistical tests to the examples listed in the table for each respective procedure.

**Table 1**

**Parametric Statistical Tests and the Analogous Nonparametric (Equivalent) Statistical Test**

| Analysis Goal | Example | Parametric Procedure | Nonparametric Procedure |
|---|---|---|---|
| Compare means of 2 independent groups | Does mean level of class attend -ance differ by class assignment (Morn/Eve)? | Independent samples t-test | Mann-Whitney U |
| Compare two scores from the same or related individual(s) | Does class attendance increase significantly before and after a health intervention? | Paired t-test | Wilcoxon signed-rank test |
| Compare means between ≥3 independent groups | Does mean level of class attend -ance differ by Dr. Rx no, recommended, yes? | One-way ANOVA | Kruskal-Wallis test |
| Estimate the degree of assoc -iation between 2 continuous variables | Does class attendance increase at a significant level as class enjoyment scores increase? | Pearson Correlation | Spearman's rank correlation |

**Parametric Analysis with Our Small Sample (*n*=25)**

In this section we will apply the nonparametric tests listed in **Table 1** to a statistical analysis involving a small sample, which will be a subset of the larger sample of 100 community residents involved in our initial quantitative analysis. Specifically, let's assume here that we have not yet done any quantitative or qualitative analysis, but require 25 residents for a small sample study.

From the administrator's list of 100 residents, assume we have sampled every 5$^{th}$ resident from the list of 1 to 95, as well as the final last 5 residents (96 to 100) for data collection. The result are data from these 25 community residents, which will now be used in a mixed methods analysis to answer the original research questions and hypotheses posed to us by the administrators.

Of particular interest to us will be examining how representative the findings produced by the small sample (*n*=25) will be relative to the full sample (*n*=100). In other words, *how close* are the findings via the small sample relative to the larger group represented (*N*=100).

We can compare each numerical value and statistical finding to discover if the findings produced involving the smaller study are accurate. Here we could speculate if we could have conducted the research project involving only the 25 residents within the smaller sample concerning this mixed methods study and produced the same findings?

Before performing the bivariate analysis it may be helpful to examine how the variable distributions may have changed between the full sample of 100 and the smaller sample of 25 residents. **Table 2** presents a univariate analysis comparing the distributions of the continuous study variables among the samples of 100 and 25 community residents.

Mean scores suggest the samples are approximately similar among the larger and smaller samples regarding rates of class attendance (*M*=3.69, *SD*=1.81 and *M*=3.00, *SD*=2.05, respectively) and Age (*M*=79.29, *SD*=8.75 and *M*=84.8, *SD*=8.20, respectively), but differed quite a bit regarding level of class enjoyment (*M*=3.00, *SD*=1.40 and *M*=1.57, *SD*=1.23, respectively).

**Table 2**

**Univariate Analysis: Continuous Variables**

| | Variable | Mean (SD) | Min/ MAX | Scale Range |
|---|---|---|---|---|
| Values for the Full Sample N=100 | Class Attendance | 3.69 (1.81) | 0-7 | 0-7 |
| | Age | 79.29 (8.75) | 61-94 | NA |
| | Class Enjoyment | 3.00 (1.40) | 1.0-5.0 | 1.0-5.0 |
| Values for the Full Sample N=25 | Class Attendance | 3.00 (2.05) | 0-6 | 0-7 |
| | Age | 84.28 (8.20) | 65-94 | NA |
| | Class Enjoyment | 1.57 (1.23) | 1.0-5.0 | 1.0-5.0 |

**Table 3** presents a univariate analysis comparing the distributions of the categorical study variables among the samples of 100 and 25 community residents. The percentages of residents within categories of each categorical variable seem largely comparable with the exception of the dependent variable **Attend Class ≥3 days/week** where percentage of residents that did not attend class at this rate seemed high among the smaller sample (48%; *n*=12) relative to the full sample (29%; *n*=29).

**Table 3**

**Univariate Analysis: Categorical Variables**

| | Partial Sample N=25 | Full Sample N=100 |
|---|---|---|
| **Variable** | **n (%)** | **n (%)** |
| **Doctor Rx** | | |
| No | 13 (52.0) | 40 (40.0) |
| Recommended | 6 (24.0) | 30 (30.0) |
| Yes | 6 (24.0) | 30 (30.0) |
| **Class Assignment** | | |
| Morning | 14 (56.0) | 50 (50.0) |
| Evening | 11 (44.0) | 50 (50.0) |
| **Class Instructor** | | |
| Ms. Getinline | 13 (52.0) | 50 (50.0) |
| Ms. Allbright | 12 (48.0) | 50 (50.0) |
| **Attend Class ≥3 days/week** | | |
| No | 12 (48.0) | 29 (29.0) |
| Yes | 13 (50.0) | 71 (71.0) |

## Mann-Whitney U Test

Within our original bivariate parametric testing, we used the independent samples t-test to examine mean differences between rate of class attendance with class assignment and class instructor. **Table 1** instructs that the nonparametric equivalent of this analysis is the Mann-Whitney U. Subsequently, these tests are each applied to these analyses below.

**SPSS Output 3** presents the results of the Mann-Whitney U test examining the relationship between class attendance with class assignment. The line labeled *Asymp. Sig. (2-tailed)* in the final column within the second box indicates that this test is statistically significant ($p < .001$).

**SPSS Output 3**

**Mann-Whitney U Test Results**

**Ranks--**

| | Class Assignment | N | Mean Rank | Sum of Ranks |
|---|---|---|---|---|
| **Class Attendance** | **Morning** | 14 | 8.71 | 122.00 |
| | **Evening** | 11 | 18.45 | 203.00 |
| | **Total** | 25 | | |

**Test Statistics**

| | Class Attendance |
|---|---|
| Mann-Whitney U | 17.000 |
| Wilcox W | 122.00 |
| Z | -3.292 |
| Asymp. Sig. (2-tailed) | .001 |

Statistically Significant $p < .05$ ($p < .001$)

**SPSS Output 4** presents the results of the Mann-Whitney U test examining the relationship between class attendance and class instructor. The line labeled *Asymp. Sig. (2-tailed)* in the final column within the second box indicates that this test is statistically significant ($p < .001$).

**SPSS Output 4**

**Mann-Whitney U Test Results**

**Ranks**

| | Class Instructor | N | Mean Rank | Sum of Ranks |
|---|---|---|---|---|
| **Class Attendance** | **Ms. Getinline** | 13 | 7.00 | 91.00 |
| | **Ms. Allbright** | 12 | 19.50 | 234.00 |
| | **Total** | 25 | | |

**Test Statistics**

| | Class Attendance |
|---|---|
| Mann-Whitney U | .000 |
| Wilcox W | 91.00 |
| Z | -4.252 |
| Asymp. Sig. (2-tailed) | .000 |

Statistically Significant
$p < .05$
($p < .001$)

**Kruskal Wallis Test**

**Table 1** also presents when comparing a categorical variable with three or more categories with a continuous variable (as one would with a One-Way ANOVA when using parametric tests), the proper nonparametric test to use would be the Kruskal-Wallis test. **SPSS Output 5** presents the results of the Kruskal-Wallis test examining the relationship between doctor prescribed classes and class attendance. The line labeled *Asymp. Sig.* in the final column within the second box indicates that this test is not statistically significant as the p-value is greater than .05 ($p$=.23)

**SPSS Output 5**

**Kruskal Wallis Test Results**

**Ranks**

| | Doctor Prescription Status | N | Mean Rank |
|---|---|---|---|
| **Class Attendance** | **No** | 13 | 11.69 |
| | **Recommended** | 6 | 11.50 |
| | **Yes** | 6 | 17.33 |
| | **Total** | 25 | |

**Test Statistics**

| | Class Attendance |
|---|---|
| Chi-square | 2.751 |
| df | 2 |
| Asymp. Sig. | .253 |

Not Statistically Significant
$p > .05$
($p = .25$)

**Spearman's Rho Test**

Finally, **Table 1** informs us that the Spearman's rank correlation (**Spearman's Rho**) can be used to test the association between two continuous variables when a parametric test of correlation is not practical. **SPSS Output 6** presents the results of the Spearman's rank correlation test comparing age and class enjoyment with class attendance.

We can see that along the second row addressing the variable *Class Attendance*, within the second line labeled *Sig (2 tailed)*, the intersecting column for age and class enjoyment have p-values above .05 (.75 and .78, respectively), indicating that these relationships are not statistically significant.

**SPSS Output 6**

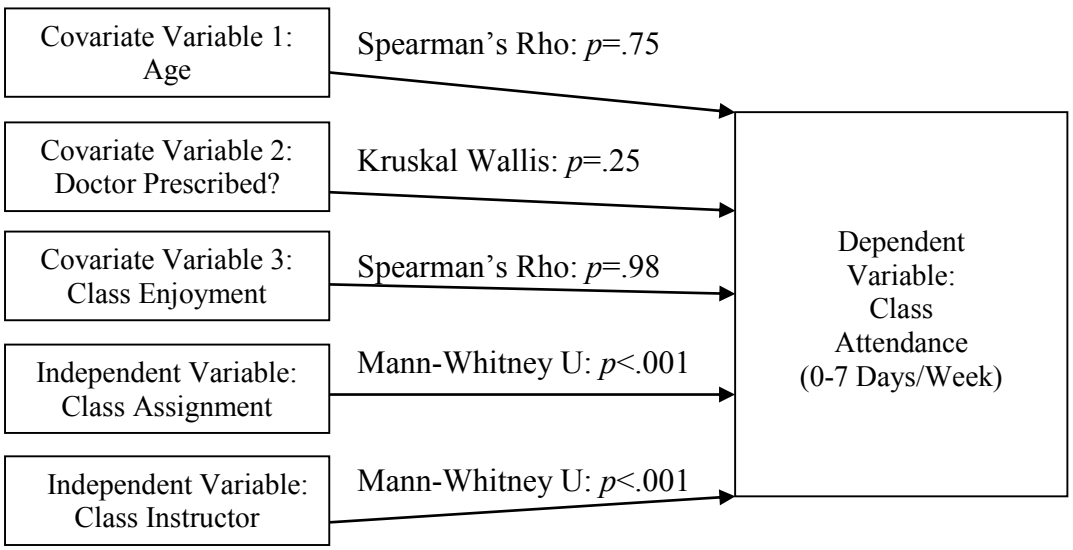
**Spearman's Rho Test**

**Not Statistically Significant**

| | | | Class Attendance | Age | Enjoy Class |
|---|---|---|---|---|---|
| **Spearman's Rho** | **Class Attendance** | Corr. Coef. | 1 | -.068 | .006 |
| | | Sig (2 tailed) | | .748 | .976 |
| | | N | 25 | 25 | 25 |
| | **Age** | Corr. Coef. | -.068 | 1 | -.357 |
| | | Sig (2 tailed) | .748 | | .080 |
| | | N | 25 | 25 | 25 |
| | **Enjoy Class** | Corr. Coef. | .006 | -.357 | 1 |
| | | Sig (2 tailed) | .976 | .080 | |
| | | N | 25 | 25 | 25 |

**Figure 7**

**Results of Nonparametric Testing**



## Results of Nonparametric Testing

**Figure 7** presents the results of the nonparametric testing. Analysis indicated that only the independent variables *Class Assignment* and *Class Instructor* are related to the dependent variable Class Attendance at a statistically significant level. Notice again, this series of nonparametric tests are the equivalent of parametric bivariate testing, which presents a problem.

Specifically, there no multivariate test to indicate the *strongest predictor* (Class Assignment/Instructor) of *Class Attendance*. Therefore, due to the limitations of nonparametric testing we cannot answer the RQs and Hypotheses. Here we cannot answer if the IV *Class Assignment* or IV *Class Instructor* is the strongest predictor of DV *Class Attendance.* This is a big problem as data indicated the IV *Class Instructor* predicts *the* DV *Class Attendance* at a level that makes IV *Class Assignment* no longer significant. Essentially, the underlying message of the data will be missed if only nonparametric (bivariate level) tests are used.

## Combining Parametric & Nonparametric Testing

Combining parametric/nonparametric tests to examine the data (via the 25 residents) will allow us to examine the data in a much more thorough manner. A careful analysis will incorporate listing the strengths, limitations, and reasons involved in using both methods. To do this, we need to repeat the quantitative bivariate analysis (from week 2) using the smaller sample of 25 community residents to examine if findings differ when compared to the nonparametric analysis. If the findings match, we will have **corroborating evidence** that the independent variables are associated with the dependent variable at a significant level and warrant inclusion in multivariate analysis.

### Independent Samples T-Test: Class Assignment/Instructor and Class Attendance

Parametric bivariate analysis must again examine if there is a significant difference in mean levels of Class Attendance by Class Assignment and Class Instructor. Keep in mind the test assumptions that must be examined for an independent samples t-test include independence of observations, no undue influence of outlier scores, a normal distribution, and homoscedasticity. Furthermore, there is a need to pay attention to how participants are dispersed within cells, e.g., *30 participants per cell* provides 80% power to detect a medium/large effect size.

**SPSS Output 7** presents an independent samples t-test examining mean score differences of *Class Attendance* by *Class Assignment*. The center column in the second box labeled *Sig. (2-tail)* reports the difference is statistically significant ($p<.001$). Within the top box, the column labeled *Mean* indicates that the evening class has a significantly higher mean level of weekly attendance relative to the morning class ($M=4.59$, $SD=1.55$ vs. $M=1.76$, $SD=1.44$, respectively).

**SPSS Output 7**

**T-TEST RESULTS**

| | Class Assigned | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Class Attendance | Morning | 14 | 1.7571 | 1.44100 | .38512 |
| | Evening | 11 | 4.5909 | 1.55528 | .46894 |

| | | Levene Test | | t-test for Equality of Means | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tail) | Mean Diff. | 95% CI Lower | Upper |
| Class Attendance | Equal variance assumed | .03 | .87 | -4.7 | 23 | .000 | 2.8 | -4.1 | -1.6 |
| | Equal variance not assumed | | | -4.7 | 20.8 | .000 | 2.8 | -4.1 | -1.6 |

**SPSS Output 8** presents an independent samples t-test examining mean score differences of *Class Attendance* by *Class Instructor*. The center column in the second box labeled *Sig. (2-tail)* reports the difference is statistically significant ($p<.001$). Within the top box, the column labeled *Mean* indicates that the Ms. Allbright has a significantly higher mean level of weekly attendance relative to Ms. Getinline ($M=4.59$, $SD=1.55$ vs. $M=1.76$, $SD=1.44$, respectively).

**SPSS Output 8**

| | Class Instructor | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Class Attendance | Ms. Getinline | 13 | 1.2538 | .93952 | .26058 |
| | Ms. Allbright | 12 | 4.9000 | .80340 | .23192 |

| | | Levene Test | | t-test for Equality of Means | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tail) | Mean Diff. | 95% CI Lower | Upper |
| Class Attendance | Equal variance assumed | .46 | .51 | -10.4 | 23 | .000 | 3.6 | -4.4 | -2.9 |
| | Equal variance not assumed | | | -10.5 | 22.9 | .000 | 3.6 | -4.4 | -2.9 |

**ANOVA (One-Way): Doctor Prescribing Class and Class Attendance**

A One-Way ANOVA is used to test if a significant difference exists regarding Class Attendance (mean scores) by Dr. Prescribing class. Recall, test assumptions for One-Way ANOVA include independence of observations, no undue influence of outliers scores, normal distribution, and homoscedasticity. Additionally, it is necessary to pay attention to how participants are dispersed within cells as 30 cases per cell produces 80% power to detect a medium/large effect, 14 cases per cell produces 80% power to detect a large effect, and 7 cases per cell produces 50% power to detect a large effect.

This is noteworthy as you will see a large difference in mean scores (i.e., Yes=Mean: 4.00 vs. Recommended=Mean: 2.55 and No=Mean: 2.75), but the overall test presented in **SPSS Output 9** is not statistically significant ($p$=.40) largely due to a lack of statistical power. Recall, 7 cases per cell gives 50% power (standard = 80%) to detect a *large* effect size. Since we have less than 7 cases in two cells, we see this test is significantly underpowered.

**SPSS Output 9**

**ANOVA RESULTS**

| Class Attendance | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|
| No | 13 | 2.75 | 2.18 | .60 |
| Recommend | 6 | 2.55 | 1.63 | .66 |
| Yes | 6 | 4.00 | 2.12 | .87 |
| Total | 25 | 3.00 | 2.05 | .41 |

**ANOVA**
Class Attend

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 8.00 | 2 | 4.00 | .95 | .40 |
| Within Groups | 92.65 | 22 | 4.21 | | |

Does not achieve statistical significance where $p$=.40

**Correlation (Pearson's r): Age and Class Enjoyment with Class Attendance**

A Pearson's correlation would be the appropriate parametric test to apply to examine if *Class Attendance* is related to *Age* and *Class Enjoyment* at a statistically significant level. Recall, the test assumptions for a parametric correlation include linearity, no undue influence of outlier scores, and a normal distribution.

**SPSS Output 10** presents the results of the correlation analysis. We can see that along the second row addressing the variable *Class Attendance*, within the second line labeled *Sig (2 tailed)*, the intersecting column for age and class enjoyment have p-values above .05 (.79 and .66, respectively), indicating that these relationships are not statistically significant.

**SPSS Output 10**

**Pearson's r Correlation Results**

**Not Statistically Significant**

| | | | Class Attendance | Age | Enjoy Class |
|---|---|---|---|---|---|
| **Pearson's r** | **Class Attendance** | Corr. Coef. | 1 | .057 | .092 |
| | | Sig (2 tailed) | | .787 | .661 |
| | | N | 25 | 25 | 25 |
| | **Age** | Corr. Coef. | -.057 | 1 | -.683** |
| | | Sig (2 tailed) | .787 | | .000 |
| | | N | 25 | 25 | 25 |
| | **Enjoy Class** | Corr. Coef. | .092 | -.683** | 1 |
| | | Sig (2 tailed) | .661 | .000 | |
| | | N | 25 | 25 | 25 |

**$p$<.01

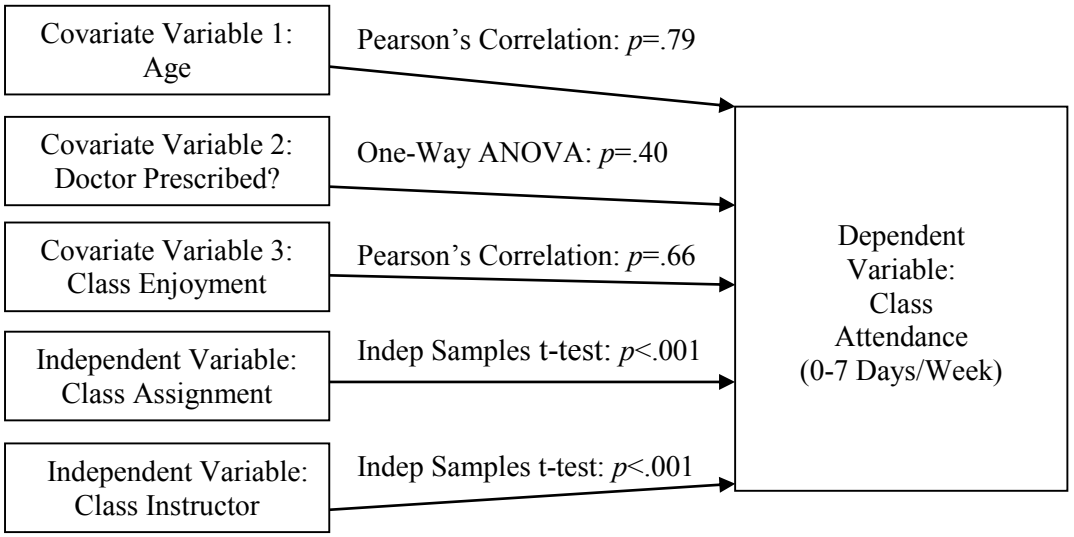
**Results of the Parametric Bivariate Analysis**

Using a small sample ($n$=25) parametric/nonparametric bivariate analysis produced similar results, as each method indicated that only *Class Assignment* and *Class Instructor* were significantly related to *Class Attendance*. Please see **Figure 8** for more detail.

However, findings differed from the initial bivariate analysis in week 2 using the full sample ($N$=100). Recall, the initial analysis indicated the CV *Dr. Rx* and CV *Class enjoyment* were also significant predictors of *Class Attendance*. However, the parametric and nonparametric analyses using the small sample ($n$=25) each failed to detect these relationships. This is likely due to low statistical power (to detect even a large effect size), small to medium effect size between the CVs and DV, or that the cases driving initial findings (i.e., the 75) were not present in these later analyses. Keep in mind also that the bivariate relationships detected using the small sample had large IV/DV effect sizes. Otherwise, we may not have seen these relationships either.

**Figure 8**

**Results of Nonparametric Testing**




## Multivariate Analysis

Next, multivariate analysis (MLR) may be used to compare the relative strength of the independent variables *Class Assignment* and *Class Instructor* with the dependent variable *Class Attendance*, to identify which of these significant predictors is the strongest predictor of *Class Attendance*. **Table 4** presents the results of the multiple linear regression model examining class attendance involving the partial sample of 25 residents.

**Table 4**

**Multiple Linear Regression Examining Class Attendance (n=25)**

| Variable | B (*SE*) | β | Sig | PES |
|---|---|---|---|---|
| Class Assignment | .10 (*.56*) | .02 | .87 | .00 |
| Class Instructor | 3.57 (*.55*) | .89 | .00 | .66 |

**Model = $F(24)=51.66$, $p<.001$, $R^2=.82$, Adjusted $R^2=.81$**

Data indicated that within this statistically significant model, $F(24)=51.66$, $p<.001$, *Class Instructor* was the strongest predictor of *Class Attendance*. Regarding statistical significance and effect size, these findings match the initial study of 100 residents, as the IV *Class Instructor* is the strongest significant predictor ($p<.001$, PES=.66) of the DV *Class Attendance* (0-7 Days).

Also identical to the findings of the initial study of 100 residents, when the IV *Class Instructor* is entered into the model, the IV *Class Assignment* is no longer significantly related to the DV *Class Attendance* (0-7 Days). Also noteworthy, the $R^2$ (=.82) is rather high, suggesting these 2 variables account for 82% of the variance in *Class Attendance,* which is unlikely. This overestimation is likely due to error related to the small sample. However, even though the $R^2$ isn't believable, it does suggest a large effect.

**Results of the Small Sample Statistical Analysis**

Findings involving the small sample reflected the primary findings of the initial study where at the bivariate level the IV *Class Assignment* and IV *Class Instructor* were significant predictors of the DV *Class Attendance* (0-7 days). At the multivariate level the IV *Class Instructor* was the strongest significant predictor of the DV *Class Attendance* (0-7 days). Also, at the multivariate level the IV *Class Instructor* cancelled the significance of IV *Class Assignment* in the regression model. However, analysis via small sample failed to detect certain sig. relationships, i.e., CVs *Dr. Rx/Class Enjoyment* with DV. Although, the RQs and hypotheses did garner the same conclusions using the full and smaller samples.

When publishing findings in a report or manuscript, consider presenting the parametric results, but also note how nonparametric tests were used to support the analysis as such: Due to the relatively small sample size involved in this study, certain assumptions of parametric tests were not met (list which if any were not met). Therefore, nonparametric tests, where these assumptions did not apply, were used to examine bivariate variable relationships. Nonparametric analysis indicated like findings relative to parametric testing (e.g., same significant relations). Therefore, it seems parametric tests were *robust*.

## Results of Small Sample Qualitative Analysis

Earlier we pondered if we would reach saturation and redundancy (the point at which data collection would end as there are no new themes and subthemes emerging from the qualitative data) with a portion of the sample instead of the full 100 residents. **Table 5** presents for comparison the percentages of residents within each theme/subtheme between the smaller (25) and full (100) samples. It seems rather apparent that the percentages or residents that indicated data reflecting each theme and subtheme are quite comparable within the partial and full sample. In end, the data do seem to suggest saturation and redundancy were reached with the smaller sample.

**Table 5**

**Qualitative Analysis: Matching Results between the Partial and Full Samples**

| | **Small Sample *n*=25** | | **Full Sample *n*=100** | |
|---|---|---|---|---|
| **CODES/CATEGORIES** | **n** | **(%)** | **n** | **(%)** |
| **Things to encourage attendance (Theme 1)** | **23** | **(92)** | **90** | **(90)** |
| Instructor preference/Prefer Ms. Allbright (subtheme 1) | 18 | (72) | 77 | (77) |
| Morning class preference (subtheme 2) | 19 | (76) | 85 | (85) |
| Positive instructor traits (subtheme 3) | 15 | (60) | 55 | (55) |
| **Barriers to attendance (Theme 2)** | **19** | **(76)** | **65** | **(65)** |
| Negative instructor traits (subtheme 1) | 4 | (16) | 15 | (15) |
| Lack of interest in class (subtheme 2) | 7 | (28) | 25 | (25) |
| Drawbacks to evening class (subtheme 3) | 5 | (20) | 19 | (19) |
| Physical demands of class (subtheme 4) | 4 | (16) | 10 | (10) |

## Other Options for Analysis Involving Small Samples

Another option for identifying appropriate methods to examine data derived from small samples is to consider using a dichotomous dependent variable. Recall, in examining the dichotomous dependent variable *Class Attendance* (≥3 days/week), the primary statistical tests of association used were the **Chi-square** and **Binary Logistic Regression.**

Well, the **Chi-square** is a nonparametric test with few assumptions. **Binary logistic regression** has fewer assumptions than MLR, so the method may accommodate a smaller sample better. Thus, analysis involving a small sample can often be more straightforward with a **dichotomous dependent variable.** Specifically, the researcher does not need many nonparametric substitutes, as bivariate analysis uses the nonparametric chi-square with either small or large samples. Furthermore, the **binary logistic regression** does not have many tests assumptions, such as a normal distribution, etc. In several ways, the analysis is the same whether small or large samples are being involved.

## In Conclusion

Nonparametric analysis was used to address the limitations posed by research involving a small sample. Nonparametric tests have useful, but limited applications. Regarding our study, nonparametric analysis was effective in answering the RQs and hypotheses when used in combo with parametric tests. In end, we can state that an effective statistical analysis is possible even when conducting research involving a small sample size ($n$<30).