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

CLASS 4:

ESSENTIALS OF MIXED METHODS RESEARCH

Welcome to week four 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

A **mixed methods research design** is a procedure for collecting, analyzing, and "mixing" both quantitative and qualitative data in a single study to understand a research problem (Creswell, 2013). A mixed methods research design is useful when both quantitative and qualitative data, together, provide a better understanding of your research problem. In essence, a mixed method design is often a terrific way to obtain a deeper version of the perspective of a study participant and a more complete picture of a research problem.

Briefly, the quantitative research component may suggest the data trends and inferential variable relationships within a population, while the qualitative data reflects the context of the topic under study in the participants' own words. The mixed methods design is useful in many instances, such as building from one phase of a study to another (e.g., an initial quantitative investigation with a qualitative follow-up or vice versa).

Creswell (2013) has suggested 7 steps when conducting a mixed methods study. **Figure 1** presents the seven steps we will consider when conducting a mixed methods study.

Figure 1

The 7 Steps of a Mixed-Methods Study

Step 1: Quantitative and Qualitative Study Map

Step 2: Determine if a Mixed-Methods Study is Feasible

Step 3: Identify a Rationale for a Mixed-Methods Study

Step 4: Select a Mixed Methods Study Design

Step 5: Collect Qualitative and Quantitative Data

Step 6: Analyze Data

Step 7: Write-Up and Report

When examining these steps, one might note that steps 2-5 are largely conceptual and methodological. This might be puzzling as our webinar presentation is primarily concerned with data analysis. However, it is important to keep in mind that steps 2-5 are important to data analysis as these steps affect how the quantitative and qualitative data are merged, compared, analyzed, and so on, which impacts data analysis.

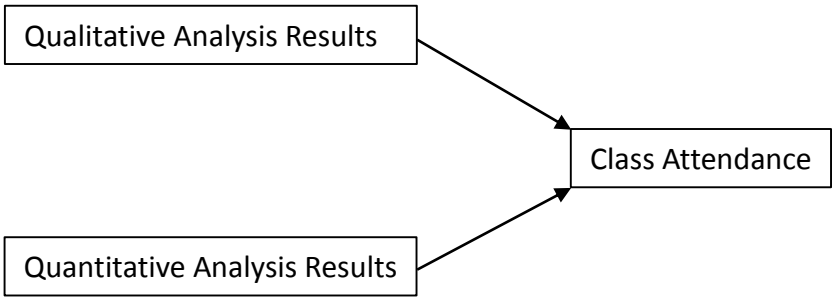
Study design is less impactful on certain forms of analysis, such as a purely quantitative study where the statistical tests needed would be quite clear relative to if a study is cross-sectional, pre/post, or longitudinal. However, having two types of data (qualitative and quantitative) involved in in a study design typically makes data analysis more complex.

Step 1: Quantitative & Qualitative Study Map

Step 1: Quantitative & Qualitative Study Map, is a chance to specify What are you going to do? Specifically, which data, e.g., covariate and independent variable(s), will be related to which dependent variable(s) or outcome(s)? In weeks 1 through 3, we provided specific study maps for our quantitative and qualitative data analysis studies. Subsequently, we may opt to construct a more general study map in our mixed methods analysis, such as the diagram presented in **Figure 2**. Here the figures presents a simple illustration describing how we will examine the direct impact of the qualitative and quantitative data strands upon the dependent variable *Class Attendance*.

Figure 2.

Step 1: Quantitative & Qualitative Study Map



Step 2: Is a Mixed-Methods Study Feasible

Step 2: Is a Mixed-Methods Study Feasible, addresses the question **Can you do it?** Specifically, there are several skills needed and potential barriers that must be addressed before one might be confident that a mixed methods study can be conducted. First, of course the researcher must have the skills to proficiently conduct both a quantitative and qualitative study and data analysis. Second, the researcher must have the necessary time and resources to collect and analyze both sets of data. Keep in mind, a typical purely qualitative or quantitative study takes a great deal of time and resources, so approaching mixed methods takes special consideration. Lastly, the researcher must consider if any of the other researchers or significant parties have any objections to combining the qualitative and quantitative methods.

Step 3: Rationale for a Mixed-Methods Study

Step 3: Rationale for a Mixed-Methods Study, asks Do you need to do it? Specifically, Step 3 requires the specification of why a mixed methods study is necessary to answering the research question(s) and hypothesis(es) effectively. For example, a mixed methods study might be appropriate when a project requires more than one data source to address the research question, to institute a follow-up qualitative or quantitative study to elaborate upon or explain an initial study, or help generalize the findings of an initial qualitative study by implementing a larger quantitative project examining the same phenomena.

Step 4: Select a Mixed Methods Study Design

Step 4: Select a Mixed Methods Study Design, asks How will you do it? Specifically, this steps requires the specification of which mixed method study design will be used to gather each strand of the data. Mixed methods study designs generally vary by four factors, which are the:

1) Level of interaction between the quantitative and qualitative data
2) Relative priority assigned to the quantitative and qualitative data
3) Timing of collecting the quantitative and qualitative data
4) Procedures for mixing the quantitative and qualitative data

These four factors are found in different combination within the four basic mixed method study design models, which are:

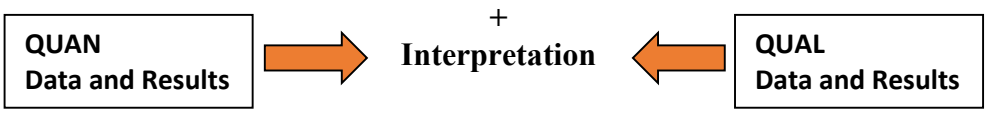
1) Convergent Parallel Design
2) Explanatory Sequential Design
3) Exploratory Sequential Design
4) Embedded Design

Basic Design Type 1: Convergent Parallel Design

Figure 3 presents the Basic Design Type 1: Convergent Parallel Design, which involves assigning equal priority to both the qualitative and quantitative data collection and analysis. Here each type of data are collected together and data are compared toward determining similar or dissimilar results.

Figure 3

Basic Design Type 1: Convergent Parallel Design



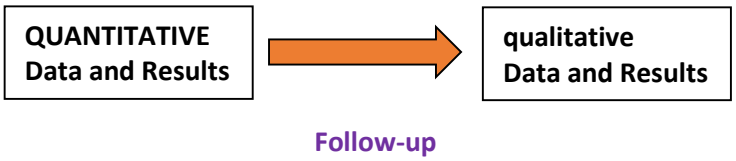
Notation System:
+ indicates the simultaneous or concurrent collection of quantitative and qualitative data
Uppercase letters indicate a priority/increased weight for either quantitative or qualitative data
Lowercase letters indicate a lower priority/weight for either quantitative or qualitative data

Basic Design Type 2: Explanatory Sequential Design

Figure 4 presents the Basic Design Type 2: Explanatory Sequential Design. Here priority is on the quantitative data collection and analysis. Specially, quantitative data are collected first in the sequence and qualitative data are used to explain the earlier quantitative data results.

Figure 4

Basic Design Type 2: Explanatory Sequential Design



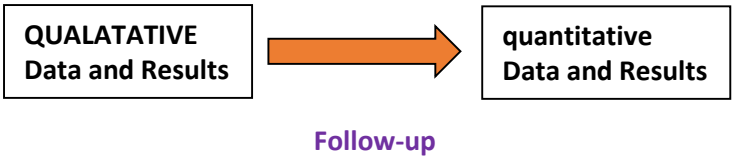
Notation System:
Uppercase letters indicate a priority/increased weight for either quantitative or qualitative data
Lowercase letters indicate a lower priority/weight for either quantitative or qualitative data

Basic Design Type 3: Exploratory Sequential Design

Figure 5 presents the **Basic Design Type 3: Exploratory Sequential Design**, where emphasis is accorded to the qualitative data rather than quantitative data. Specifically, qualitative data are collected first. Next, quantitative data are collected and used to build on or explain the initial qualitative findings.

Figure 5

Basic Design Type 3: Exploratory Sequential Design



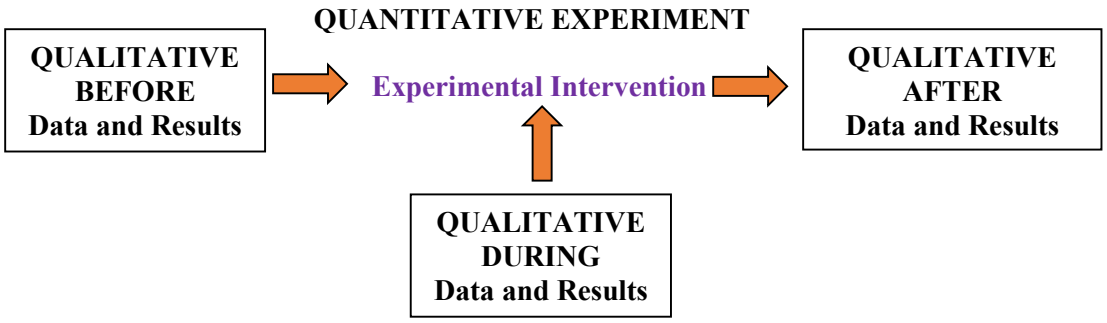
Notation System:
Uppercase letters indicate a priority/increased weight for either quantitative or qualitative data
Lowercase letters indicate a lower priority/weight for either quantitative or qualitative data

Basic Design Type 4: Embedded Design

Figure 6 presents the Basic Design Type 4: Embedded Design Emphasis, where priority can be assigned to either the qualitative or quantitative data collection or analysis. Here, one dataset may play a secondary supporting role, such as qualitative data used to examine the intervention process as presented in this figure.

Figure 6

Basic Design Type 4: Embedded Design



Step 5: Collect Qualitative and Quantitative Data

The objective of **Step 5: Collect Qualitative and Quantitative Data**, is to gather information to answer the study research question(s) and hypothesis(es). In terms of conducting a mixed methods study, there are specific challenges related to data collection that warrant mention.

First, the researcher must reconcile the tendency for qualitative research to employ purposive sampling, while quantitative research favors probabilistic sampling. Specifically, qualitative research tends to use purposive sampling where participants are selected who have experience in the central phenomena/key concept being studied. Quantitative research sampling tends to be probabilistic where a large number of participants are selected who represent the study population.

Thus, when conducting a mixed-methods study there may be a need to take special precaution to be sure each of these data collection procedures are considered. For example, from a quantitative standpoint, the researcher must be sure a sufficient number of study participants are involved in the research to generate the proper level of statistical power needed to test the study question(s) and hypothesis(es).

However, from a qualitative standpoint, the researcher must be sure the appropriate type of study participants are involved in the study toward achieving the saturation and redundancy of qualitative study data. There is not much written on mixed methods data collection, but there are important considerations

1) **Will the 2 samples (Quantitative and Qualitative) include different or the same participants?**

   Recall, our sample study collected quantitative data from 100 residents of a retirement community initially, then interviewed the same 100 residents to gather qualitative data at follow-up. Because these were the same 100 residents, we are able to make direct comparisons between the qualitative and quantitative data that each resident provided. However, it is important to consider that some research involves different individuals in providing each strand of data. There are several implications when this method is used, including the inability to connect each strand of data to a specific study participant.

2) **Will the samples (Quantitative and Qualitative) be the same size?**

Again, within our sample there is the same number of study participants involved in providing both the quantitative data (100 residents) and qualitative data (100 residents). However, having an unequal number of study participants involved with each data strand has several implications. For example, to compare the **quantitative data at timepoint 1** with the **qualitative data at timepoint 2** we need equal sample sizes. Specifically, assume data are gathered on **100 people at timepoint 1 (e.g., QUANTITATIVE DATA)** and **30 at timepoint 2 (e.g., QUALITATIVE DATA)**. Here, a direct comparison of the data gathered at times 1 and 2 will involve only **30 participants** because only 30 are common to each data strand. From a quantitative perspective this reflects a small sample for analysis. Therefore, if qualitative oriented issues such as statistical power and having a more representative sample for the study are important, the topic of such an unequal sample size should be addressed.

3) **Will the same concept be assessed quantitatively and qualitatively?**

There is also a need to decide if the same concept will be assessed quantitatively and qualitatively. For example, in our sample study, the goal of the qualitative analysis is to generate a more detailed picture of the factors influencing class attendance, to enhance the earlier quantitative findings. In this case it would have been a significant problem if the same concept was not assessed quantitatively and qualitatively. However, the goals of other research studies may differ where an assessment of different concepts using qualitative and quantitative methods may be appropriate.

Step 6: Analyze Data

Essentially, a mixed-methods data analysis involves looking across qualitative and quantitative strands of data to answer the research question(s) and hypothesis(es) more fully. Inferences in mixed methods research are conclusions or interpretations drawn from one strand of the data. However, inferences drawn from both the qualitative and qualitative data strands are referred to as **meta inferences**. The goal of the mixed method study is to improving the quality of inferences by addressing these two data sources.

Onwuegbuzie and Teddlie (2003) have suggested that mixed-methods data analysis be approached as seven separate steps. Subsequently, we will approach our mixed methods data analysis 6a-6g, as listed in **Figure 7**.

Figure 7

The 7 Steps of Step 6: Mixed-Methods Data Analysis

Step 6a: Data Reduction (Perform Quant./Qual. Data Analysis)

Step 6b: Data Display (Present Findings of Each, e.g., tables)

Step 6c: Data Transformation (Qual. Data to Quant./Vice Versa)

Step 6d: Data Correlation (Which Quant./Qual. Seems Related)

Step 6e: Data Consolidation (Combine Data Types to 1 Dataset)

Step 6f: Data Comparison (Compare Data From 2 Sources)

Step 6g: Data Integration (Analyze Data & Note Findings)

Step 6a: Data Reduction & Step 6b: Data Display

Steps 6a Data Reduction and **6b Data Display** are presented below for the final analysis and table display for both our qualitative and quantitative final analysis results. Specifically, here we will present the two regression models reflecting the final analysis of the quantitative data, as well as the table reflecting the themes and subthemes identified in qualitative analysis.

Multiple Linear Regression Model Generated In Quantitative Analysis

Table 1 presents the results regarding the multiple linear regression model generated in quantitative analysis. The text beneath the table uses a blue arrow to point to the PES effect size that identifies the **Independent Variable** *Class Assignment* ($p<.001$, PES=.22) as the strongest predictor of the **Dependent Variable** *Class Attendance* (0-7 Days).

Table 1

Multiple Linear Regression Model (Quantitative analysis)

Variable	B (*SE*)	β	Sig	PES
Age	-.00 (*.02*)	-.01	.93	.00
Dr. Rx No (Ref.)				.15
Dr. Rx Rec.	.49 (*.35*)	.13	.17	
Dr. Rx Yes	1.43 (*.35*)	.36	.00	
Enjoy Class	.39 (*.14*)	.31	.01	.08
Class Assignment	1.48 (*.29*) .41	.00	.22	

Model = $F(99)=12.56$, $p<.001$,
$R^2=.40$, Adjusted $R^2=.37$

The **Independent Variable** *Class Assignment* was the strongest predictor of the **Dependent Variable** *Class Attendance* (0-7 Days) ($p<.001$, PES=.22)

Binary Logistic Regression Model Generated In Quantitative Analysis

Table 2 presents the results regarding the binary logistic regression model generated in quantitative analysis. The text beneath the table uses a blue arrow to point to the odds ratio (OR) effect size that identifies the **Independent Variable** *Class Assignment* ($p<.001$, OR=6.44) as the strongest predictor of the **Dependent Variable** *Class Attendance* ($\geq$3 Days per week, Yes/No).

Therefore, based upon these two regression models that reflect the final quantitative statistical analysis, the **Independent Variable** *Class Assignment* (Morning/Evening) seems to be the strongest predictor of the **Dependent Variable** *Class Attendance*.

Table 2

Binary Logistic Regression Model (Quantitative analysis)

Variable	B (*SE*)	Wald	Sig.	OR	95% CI
Age	-.02 (*.04*)	.26	.93	.98	.90-1.06
Dr. Rx No (Ref.)					
Dr. Rx Rec.	.77 (*.62*)	1.54	.21	2.15	.64-7.20
Dr. Rx Yes	1.55 (*.69*)	5.09	.02	4.72	1.2-18.1
Enjoy Class	.57 (*.27*)	4.41	.04	1.74	1.0-2.93
Class Assignment	1.86 (*.57*)	10.7	.001	6.44	2.1-19.7

Model = $X^2(5)=27.93$, $p<.001$

The **Independent Variable** *Class Assignment* was the strongest predictor of the**Dependent Variable** *Class Attendance* (≤3 Days) (*p*<.001, OR=6.44)

Qualitative Data Analysis Results

Table 3 presents the results on the qualitative data analysis involved in our mixed methods study. Specifically, this table presents the two themes that have emerged within the data, which are **Things to Encourage Attendance** and **Barriers to Attendance**. The table also presents various subthemes within the theme **Things to Encourage Attendance** (i.e., Instructor preference/Prefer Ms. Allbright, Morning class preference, and Positive instructor traits), as well as the theme **Barriers to Attendance** (Negative instructor traits, Lack of interest in class, Drawbacks to evening class, and Physical demands of class).

Table 3

Themes and Subthemes Identified in Qualitative Analysis

CODES/CATEGORIES	n	(%)
Things to Encourage Attendance (Theme 1)	**90**	**90**
Instructor preference/Prefer Ms. Allbright (subtheme 1)	77	77
Morning class preference (subtheme 2)	85	85
Positive instructor traits (subtheme 3)	55	55
Barriers to Attendance (Theme 2)	**65**	**65**
Negative instructor traits (subtheme 1)	15	15
Lack of interest in class (subtheme 2)	25	25
Drawbacks to evening class (subtheme 3)	19	19
Physical demands of class (subtheme 4)	10	10

Step 6c: Data Transformation

Step 6c involves transforming the qualitative data into quantitative variables (or vice versa) in preparation for combining both sets of data into a single database for mixed methods data analysis. For example, our study will involve transforming the qualitative data themes and subthemes into quantitative variables in SPSS for inferential analysis.

Qualitative data can be transformed into quantitative variables in various forms and structures. For example, if we consider (within **Theme 1) Subtheme 3 Positive instructor traits**, we see there were three categories of responses, which are residents who described the quality *Enthusiastic*, *Calm Voice*, and *Enthusiastic and Calm Voice*. When transformed into quantitative variables these three responses might be made into **three separate Yes/No variables** as such:

- **Variable 1:** Enthusiastic (Yes/No)
- **Variable 2:** Calm Voice (Yes/No)
- **Variable 3:** Enthusiastic and Calm Voice (Yes/No)

Alternately, **Subtheme 3 Positive instructor traits** could be made into a **single categorical variable** named:

Positive Instructor Traits, with the response categories:

1) Enthusiastic

2) Calm Voice

3) Enthusiastic and Calm Voice

Notice the conversion from one single categorical variable into three Yes/No variables (and vice versa) is similar to our treatment of the quantitative variable *Dr. Prescribed Meditation Class* (Response categories: No, Recommended, Yes) and the subsequent dummy-coding of each response category.

Theme 2: Barriers to Attendance can also be converted into several types of variables using the four subtheme categories identified within this theme (i.e., Negative instructor traits, Lack of interest in class, Drawbacks to evening class, and Physical demands of class. For example, each subtheme could be made into an individual Yes/No variable:

Variable 1: Negative instructor traits (Reported: Yes/No)

Variable 2: Lack of interest in class (Reported: Yes/No)

Variable 3: Drawbacks to evening class (Reported: Yes/No)

Variable 4: Physical demands of class (Reported: Yes/No)

Likewise, **Theme 2: Barriers to Attendance** can form one categorical variable, such as:

Barriers to Attendance (with the response categories):

1) Negative instructor traits

2) Lack of interest in class

3) Drawbacks to evening class

4) Physical demands of class

A third variable derived from **Theme 2: Barriers to Attendance** could be one continuous variable reflecting the number of subthemes indicated by each resident. This continuous variable would be computed through summing the four dummy-coded Yes/No variables reflecting each subtheme, where Yes=1 and No=0. Specifically if we sum:

Negative instructor traits (Yes=1, No=0) +

Lack of interest in class (Yes=1, No=0) +

Drawbacks to evening class (Yes=1, No=0) +

Physical demands of class (Yes=1, No=0) =

We would produce a new variable with a potential range of scores from 0-4 that would reflect how many barriers each resident indicated, a.k.a., the number of subthemes each resident indicated. Quantitative analysis could then be employed to examine if the dependent or outcome variable is related to barriers to attendance structured in these several ways, as a single categorical variable, as a series of yes/no variables, or as a continuous variable.

Step 6d: Data Correlation

Step 6d involves observing data correlation. This is not done using statistical tests, but rather involves observing which variables across the qualitative and quantitative datasets appear to be related.

Perhaps the most interesting finding at this point is that the primary finding identified through the quantitative analysis is not reflected in the qualitative data. Specifically, quantitative analysis indicated that the **IV** *Class Assignment*, specifically assignment to evening classes, is the strongest predictor of the **DV** *Class Attendance*.

However, the qualitative data do not reflect that being assigned to evening classes is a factor that would encourage class attendance. Indeed the qualitative data suggest the opposite where 85% (*n*=85) of residents specifically noted that they would prefer to attend class in the morning!

Furthermore, the qualitative data have identified that the factor of *Class Instructor* (a new Independent Variable) is a salient consideration of what influences *Class Attendance*. Specifically 77% of residents have suggested that Ms. Allbright leading the class would encourage their *Class Attendance*.

Added Data Based Upon Results

Based upon the qualitative analysis, we need data regarding the variable *Class Instructor*. Subsequently, upon our asking, the residence administrators have provided data upon which instructor was assigned to teach each class during the month. The administrators also informed us, the assigned instructor for each class is printed upon each class assignment ticket, so residents can see which instructor will be leading each respective class prior to that class.

Class Instructor seems the most salient variable identified via qualitative analysis to include in the quantitative analysis. However, it also seems to make sense to examine if any of the **Barriers** in **Theme 2** have a significant impact on attendance. Thus, we will plan to include all these variables in our final single dataset.

Step 6e: Data Consolidation

Next, in Step 6e: Data Consolidation, we will combine the qualitative and quantitative data into one dataset. We will enter the qualitative data (the text comments full or partial) from the word documents into SPSS as text variables. This is quite similar to how the qualitative data are segmented and stored within qualitative software databases. Furthermore, corresponding numeric variables will be created that parallel the text variables and assign numeric values (numbers) to each comment. All qualitative data can then be presented descriptively and be included in inferential statistical analysis as needed. **The end result is one dataset (in the SPSS software)**.

Figure 8 presents a sample of text and corresponding numeric variables in the SPSS software. Through noting these variables it will become evident how the qualitative data become quantitative variables. For example, the first column on the left is named **Th2Sub1NegInst**, which stands for Theme 2 (**Th2**), Subtheme 1 (**Sub1**), and Negative Instructor Traits (**NegInst**). You will see within the cells of this column are the text responses from individual residents that qualify as data that reflect comments regarding negative instructor traits.

The column to the right is named **Th2Sub1NegInstYN**, which stands for Theme 2 (**Th2**), Subtheme 1 (**Sub1**), Negative Instructor Traits (**NegInst**), and Yes/No (**YN**). This variable flags which study participants made comments reflecting negative instructor traits Yes or No, where 1 indicates "Yes" and 0 indicates "No." You will notice where there is a comment in the variable **Th2Sub1NegInst**, there is a corresponding 1 (1=Yes) in the variable **Th2Sub1NegInstYN**. Additionally, where there is no response for the variable **Th2Sub1NegInst** (indicated by the term *No Comment*) there is a corresponding 0 (0=No) in the variable **Th2Sub1NegInstYN**.

Figure 8

Sample of Text and Corresponding Numeric Variables in the SPSS Software

Th2Sub1NegInst	Th2Sub1NegInstYN	Th2Sub2LackInterest	Th2Sub2LackInterestYN
No comment	0	I don't like the class	1
too strict	1	No comment	0
hard to relax in h	1	No comment	0
too loud for med	1	No comment	0
No comment	0	I prefer other classes	1
a little abrupt	1	No comment	0

Qualitative Data: Text responses for negative instructor trait **Variable Type: Text**

1 = Yes
0 = No
(Did the resident report a negative Instructor trait?)
Variable Type: **Numeric**

Step 6f: Data Comparison

Step 6f involves comparing the two data sources once combined into the same database. This comparison will serve several functions. For example, suppose a smaller number of study participants provided qualitative data relative to quantitative data. In this instance it would be important to compare the two datasets to be sure the smaller number of study participants that provided qualitative data represented the larger sample in terms of key characteristics, such as demographic qualities. For example, assume the full sample is 50% male and 50% female.

In this instance, it may be problematic if the smaller number of study participants who provided qualitative data were all male or all female. In either case, it is typically a good idea to run a **descriptive (univariate) analysis** that includes all the merged qualitative and quantitative variables to become familiar with the data.

Step 6g: Data Integration

Step 6g Data Integration, is the step where the actual analysis of the data occurs and the findings are presented. Within our sample study data analysis will involve how ***Class Attendance*** is impacted by **Barriers to Attendance (Theme 2)**, which are the qualitative data that were translated into quantitative variables. Data integration will also involve examining if the new **Independent Variable** *Class Instructor* is related to the **Dependent Variable** *Class Attendance* at a statistically significant level. Variables related to *Class Attendance* at the bivariate level at a statistically significant level will be entered into the regression models (multiple linear/binary logistic) initially created in week two of this program in quantitative analysis.

Examining *Class Attendance* (0-7 days per week)

In order to test the quantitative variables (derivative from the qualitative data) to determine which are significantly related to the **Dependent Variable** *Class Attendance* (0-7 days per week), we will apply the bivariate test key, as presented in **Figure 9**. **Figure 10** presents the bivariate test key with the newly formed quantitative study variables plugged in. You will see that the correct bivariate test needed to test each relationship is specified for each new variable relationship.

Figure 9 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 10 Bivariate Test Key (Study Variables Plugged In)

Variable 1	Variable 2	Test To Use
Categorical (2)	Continuous	t-test
≥1 Barriers (Yes/No)	Class Attend (0-7)	t-test
Class Inst. (Get/All)	Class Attend (0-7)	t-test
Categorical (>2)	Continuous	ANOVA
Barriers (Categories)	Class Attend (0-7)	ANOVA
Continuous	Continuous	Correlation
# Barriers (0-4)	Class Attend (0-7)	Correlation

Recall that instructions to conduct each of these bivariate tests are presented in detail in the quantitative analysis portion (Week 2) of our 6 week webinar presentation. After applying the statistical tests specified within **Figure 10**, the only predictor related to the **Dependent Variable** *Class Attendance* (0-7 days per week) is the **Independent Variable** *Class Instructor*. **Statistical Output 1** presents the results of the independent samples t-test analysis relating how the average number of days attending class per week differs by class instructor. The bottom box in the output includes a column in the center labeled **Sig. (2-tail)**, which is highlighted. This column reflects that the relationship is statistically significant as the p-value is below .05 (p<.001).

The column in the center box on the top (highlighted) labeled **Mean,** presents the mean number of days residents attended class per week according to each instructor. The numbers indicate that the average resident attended class with Ms. Getinline about two and a half (M=2.42. SD=1.16) days per week. Additionally, the average resident attended classes instructed by Ms. Allbright almost five (M=4.95, SD=1.41) days per week. Subsequently, we can state that there is s statistically significant difference in mean scores that reflect on average residents attend Ms. Allbright's classes nearly five days per week and attend Ms. Getinline's class about two and a half days per week.

Statistical Output 1

T-TEST RESULTS

	Class Instructor	N	Mean	Std. Deviation	Std. Error Mean
Class Attendance	Ms. Getinline	50	2.42	1.16	.16
	Ms. Allbright	50	4.95	1.41	.20

		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	.45	.51	-9.8	98	.000	-2.5	-3.1	-2.0
	Equal variance not assumed			-9.8	94	.000	-2.5	-3.1	-2.0

Examining *Class Attendance* (Attend Class ≥3 days per week)

In order to test the quantitative variables (derivative from the qualitative data) to determine which are significantly related to the **Dependent Variable** *Class Attendance* (attend class ≥3 days per week), we will apply the bivariate test key, as presented in **Figure 9**. **Figure 11** presents the bivariate test key with the newly formed quantitative study variables plugged in. You will see that the correct bivariate test needed to test each relationship is specified for each new variable relationship.

Figure 11 Bivariate Test Key (Study Variables Plugged In)

Variable A (IV/CV)	Variable B (DV)	Test
Continuous	Categorical (2 cat.)	t-test
# Barriers (0-4)	Class Attend (≥3 day)	t-test
Categorical	Categorical	Chi-Square
Class Inst. (Get./All.)	Class Attend (≥3 day)	Chi-Square
Barriers (Categories)	Class Attend (≥3 day)	Chi-Square
≥1 Barriers (Yes/No)	Class Attend (≥3 day)	Chi-Square

Recall that instructions to conduct each of these bivariate tests are presented in detail in the quantitative analysis portion (Week 2) of our 6 week webinar presentation. After applying the statistical tests specified within **Figure 11**, the only predictor related to the **Dependent Variable** *Class Attendance* (attend class ≥3 days per week) is the **Independent Variable** *Class Instructor*. **Statistical Output 2** presents the results on the chi-square analysis examining if residents attending class 3 days per week or more (Yes/No) differs by class instructor at a statistically significant level. The bottom box in the output includes a third column labeled **Asymp. Sig. (2-Sided)**, which is highlighted. This column reflects that the relationship is statistically significant as the p-value is below .05 ($p<.001$).

The center column in the top box in the output is labeled *Attend Class ≥3 Days*. The subcolumn beneath this label marked *Yes* (which is highlighted) indicates that 50% ($n=25$) of the residents attend Ms. Getinline's classes 3 or more days per week. However, regarding Ms. Allbright's classes, 92% ($n=46$) of residents attend class 3 or more days per week. In essence, when residents have the opportunity to attend Ms. Allbright's classes, almost all (92%) of them attend class 3 or more days per week. However, if residents have passes for Ms. Getinline's class, only half (50%) attend class 3 or more days per week.

Statistical Output 2

CHI-SQUARE RESULTS

			Attend Class ≥3 Days		Total
			No	Yes	
Class Instructor	Ms. Getinline	Count	25	25	50
		% within instructor	50.0%	50.0%	100.0%
	Ms. Allbright	Count	4	46	50
		% within instructor	8.0%	92.0%	100.0%
Total		Count	50	50	100
		% within instructor	50.0%	50.0%	100.0%

	Value	df	Asymp. Sig. (2-Sided)
Pearson's Chi-Square	21.42	1	.001

Merged Analysis Results: Multiple Linear Regression

In light of the fact that the **Independent Variable** *Class Instructor* evidenced a statistically significant effect upon the **Dependent Variable** *Class Attendance* (0-7 days per week) at the bivariate level, it is necessary to reproduce the multiple linear regression model from our quantitative analysis with the new **Independent Variable** *Class Instructor* included.

Table 4 presents the **Merged Analysis Results: Multiple Linear Regression** with this full set of variables. We see that the full regression model remains statistically significant, $F(99)=43.45$, $p<.001$. Furthermore, **Independent Variable** *Class Instructor* has become the strongest predictor (PES=.56, $p<.001$) of the **Dependent Variable** *Class Attendance* (0-7 days per week).

Table 4

Merged Analysis Results: Multiple Linear Regression

Variable	B (*SE*)	β	Sig	PES
Age	-.01 (*.02*)	-.05	.47	.00
Dr. Rx No (Ref.)				.28
Dr. Rx Rec.	.43 (*.24*)	.11	.07	
Dr. Rx Yes	1.44 (*.23*)	.37	.00	
Enjoy Class	.38 (*.09*)	.30	.00	.16
Class Assignment	.32 (*.22*) .09	.15	.03	
Class Instructor	2.39 (*.22*) .66	.00	.56	

Model = $F(99)=43.45$, $p<.001$, $R^2=.74$, Adjusted $R^2=.72$

The **Independent Variable** *Class Instructor* was the strongest predictor of the **Dependent Variable** *Class Attendance* (0-7 Days) ($p<.001$, PES=.56)

Table 5 presents the comparison between the quantitative multiple linear regression model 1 and the merged multiple linear regression model 2. We see that when added to model 2, the **Independent Variable** *Class Instructor* not only became the strongest predictor (PES=.56, $p<.001$) of the **Dependent Variable** *Class Attendance* (0-7 days per week), but the added variable also resulted in the other **Independent Variable** *Class Assignment* in becoming no longer statistically significant.

Specifically, when the **Independent Variable** *Class Instructor* was added to the model, the p-value for the **Independent Variable** *Class Assignment* changed from $p<.001$ in model 1 to $p=.15$ in model 2. Thus, the addition of the **Independent Variable** *Class Instructor* to the regression model resulted in cancelling the significance of the **Independent Variable** *Class Assignment* in explaining the **Dependent Variable** *Class Attendance* (0-7 days per week).

Table 5

Comparison: Quantitative MLR Model 1 & the Merged MLR Model 2

MLR Model 1

Variable	B (*SE*)	β	Sig	PES
Age	-.00 (*.02*)	-.01	.93	.00
Dr. Rx No (Ref.)				.15
Dr. Rx Rec.	.49 (*.35*)	.13	.17	
Dr. Rx Yes	1.43 (*.35*)	.36	.00	
Enjoy Class	.39 (*.14*)	.31	.01	.08
Class Assignment	1.48 (*.29*)	.41	.00	.22

MLR Model 2

Variable	B (*SE*)	β	Sig	PES
Age	-.01 (*.02*)	-.05	.47	.00
Dr. Rx No (Ref.)				.28
Dr. Rx Rec.	.43 (*.24*)	.11	.07	
Dr. Rx Yes	1.44 (*.23*)	.37	.00	
Enjoy Class	.38 (*.09*)	.30	.00	.16
Class Assignment	.32 (*.22*)	.09	.15	.03
Class Instructor	2.39 (*.22*)	.66	.00	.56

Note. When the effect of the predictor *Class Instructor* is considered in **MLR model 2** the IV *Class Assignment* (Strongest in MLR Model 1) is no longer significantly related to the **DV** *Class Attendance* (0-7 Days), where *p*=.15

In **MLR model 2** the IV *Class Instructor* is the strongest predictor of the **DV** *Class Attendance* (0-7 Days) (*p*<.001, PES=.56)

Merged Analysis Results: Binary Logistic Regression

In light of the fact that the **Independent Variable** *Class Instructor* evidenced a statistically significant effect upon the **Dependent Variable** *Class Attendance* (attend class ≥3 days per week) at the bivariate level, it is necessary to reproduce the binary logistic regression model from our quantitative analysis with the new **Independent Variable** *Class Instructor* included.

Table 6 presents the **Merged Analysis Results: Binary Logistic Regression** with the full set of variables. We see that the full regression model remains statistically significant, $X^2(6)=46.82$, $p<.001$. Furthermore, **Independent Variable** *Class Instructor* has become the strongest predictor (OR=18.3, 95% CI= 4.0-84.4, $p<.001$) of the **Dependent Variable** *Class Attendance* (attend class ≥3 days per week).

Table 6

Merged Analysis Results: Binary Logistic Regression

Variable	B (*SE*)	Wald	Sig.	OR	95% CI
Age	-.06 (*.05*)	1.29	.26	.94	.85-1.04
Dr. Rx No (Ref.)					
Dr. Rx Rec.	.90 (*.71*)	1.59	.21	2.45	.61-9.87
Dr. Rx Yes	2.16 (*.85*)	6.39	.05	8.63	1.6-46.0
Enjoy Class	.61 (*.31*)	3.96	.05	1.85	1.0-3.37
Class Assignment	1.07 (*.70*)	2.35	.13	2.92	.74-11.5
Instructor	2.91 (*.78*)	14.0	.001	18.3	4.0-84.4

Model = $X^2(6)=46.82$, $p<.001$

The **Independent Variable** *Class Instructor* was the strongest predictor of the **Dependent Variable** *Class Attendance* (≤3 Days) ($p<.001$, OR=18.3)

Table 7 presents the comparison between the quantitative binary logistic regression model 1 and the merged binary logistic regression model 2. We see that when added to model 2, the **Independent Variable** *Class Instructor* not only became the strongest predictor (OR=18.3, 95% CI= 4.0-84.4, $p<.001$) of the **Dependent Variable** *Class Attendance* (attend class ≥3 days per week), but the added variable also resulted in the other **Independent Variable** *Class Assignment* in becoming no longer statistically significant.

Specifically, when the **Independent Variable** *Class Instructor* was added to the model the p-value for the **Independent Variable** *Class Assignment* changed from $p<.001$ in model 1 to $p=.13$ in model 2. Thus, the addition of the **Independent Variable** *Class Instructor* to the regression model resulted in cancelling the significance of the **Independent Variable** *Class Assignment* in explaining the **Dependent Variable** *Class Attendance* (attend class ≥3 days per week).

Table 7

Comparison: Quantitative BLR Model 1 & the Merged BLR Model 2

BLR Model 1

Variable	B (*SE*)	Sig.	OR	95% CI
Age	-.02 (*.04*)	.93	.98	.90-1.06
Dr. Rx No (Ref.)				
Dr. Rx Rec.	.77 (*.62*)	.21	2.15	.64-7.20
Dr. Rx Yes	1.55 (*.69*)	.02	4.72	1.2-18.1
Enjoy Class	.57 (*.27*)	.04	1.74	1.0-2.93
Class Assignment	1.86 (*.57*)	.001	6.44	2.1-19.7

BLR Model 2

Variable	B (*SE*)	Sig.	OR	95% CI
Age	-.06 (*.05*)	.26	.94	.85-1.04
Dr. Rx No (Ref.)				
Dr. Rx Rec.	.90 (*.71*)	.21	2.45	.61-9.87
Dr. Rx Yes	2.16 (*.85*)	.05	8.63	1.6-46.0
Enjoy Class	.61 (*.31*)	.05	1.85	1.0-3.37
Class Assignment	1.07 (*.70*)	.13	2.92	.74-11.5
Instructor	2.91 (*.78*)	.001	18.3	4.0-84.4

Note. When the effect of the predictor *Class Instructor* is considered in BLR model 2 the IV *Class Assignment* (Strongest in MLR Model 1) is no longer significantly related to the DV *Class Attendance* (≥3 Days), where *p*=.13

In BLR model 2 the IV *Class Instructor* is the strongest predictor of the DV *Class Attendance* (≥3 Days) (*p*<.001, OR=18.3)

Predicting the Dependent Variable *Over and Above* Another Predictor

When a predictor is added to a regression model and cancels out another predictor by making that factor no longer related to the dependent variable at a statistically significant level, the new predictor has **explained the variance** in the dependent variable formerly explained by the original significant predictor. In this case, one could say the new predictor predicts the dependent variable *over and above* the cancelled predictor.

Our quantitative analysis identified the new **Independent Variable** *Class Instructor* explained the variance in the **Dependent Variable** *Class Attendance* formerly explained by the **Independent Variable** *Class Assignment*. From a practical standpoint, it may be stated that when the researcher considers which instructor is leading the class (i.e., the **Independent Variable** *Class Instructor*), the assignment of class to the evening or morning (the **Independent Variable** *Class Assignment*) no longer matters in explaining the **Dependent Variable** *Class Attendance*.

The Independent Variable *Class Instructor* as a Confounding Variable

The qualitative analysis was essential to this study as the method identified what is known as a *Confounder Variable*. *Confounder Variables* are commonly identified as primary reasons why study results are distorted or incorrect. A confounder variable is often a key factor in explaining the variable relationships within a study. Many times this variable is not included in analysis and it is speculated that the study results may be inaccurate due the exclusion of this variable. Confounder variables are also related to both the independent and dependent variables. In terms of the initial quantitative analysis, the **Independent Variable** *Class Instructor* would be a confounding variable if it was significantly related to both the **Independent Variable** *Class Assignment* and the **Dependent Variable** *Class attendance*.

The regression models presented in **Table 4** and **Table 6** clearly identify that the **Independent Variable** *Class Instructor* is related to the **Dependent Variable** *Class attendance* at a statistically significant level. Furthermore, the chi-square analysis presented in **Statistical Output 3** also evidences that the **Independent Variable** *Class Instructor* is also associated with the **Independent Variable** *Class Assignment* at a statistically significant level ($p<.01$). The analysis revealed that Ms. Getinline taught a significantly higher percentage of classes in the morning (74%) and Ms. Allbright lead a significantly higher percentage of classes in the evening (74%). It is important to note that variables do not need to be confounders to negatively impact study results, but presence of an *unaccounted for* confounder variable is often especially egregious.

Statistical Output 3

CHI-SQUARE RESULTS

			Class Assignment		Total
			Morning	Evening	
Class Instructor	Ms. Getinline	Count	37	13	50
		% within instructor	74.0%	26.0%	100.0%
	Ms. Allbright	Count	13	37	50
		% within instructor	26.0%	74.0%	100.0%
Total		Count	50	50	100
		% within instructor	50.0%	50.0%	100.0%

	Value	df	Asymp. Sig. (2-Sided)
Pearson's Chi-Square	23.04	1	.001

In light of the usefulness of mixed methods in this study, it is important to state that both qualitative and quantitative methods may not be needed for every study. However, it is also imperative to consider two things would have occurred if both qualitative and quantitative methods were not used in this instance, which are:

1) The wrong decision regarding moving all the classes to the evening would have been recommended based purely upon the **quantitative analysis**

   Recall, the pure quantitative analysis suggested classes should all be moved to the evening because the **IV** *Class Assignment* indicated that assignment to evening class was the strongest predictor of the **DV** *Class Attendance*

2) Based purely upon **qualitative analysis** the data would be inconclusive regarding if all classes should or should not be moved to the evening

   Qualitative analysis identified **themes** reflecting both the **IV** *Class Instructor* and **IV** *Class Assignment* are related to the **DV** *Class Attendance.* However, **qualitative analysis** could not identify which **IV** trumped the other, which informed the correct decision

In end, **qualitative analysis** was instrumental in identifying the **IV** *Class Instructor* (formerly unidentified in analysis) was related to the **DV** *Class Attendance*. However, once identified, **quantitative analysis** was instrumental in identifying that the **IV** *Class Instructor* was the strongest predictor of the **DV** *Class Attendance*. Thus, without both strands of data, the results could not have answered the RQs correctly.

Lastly, regarding the final step of a mixed methods study, **Step 7: Write-Up and Report**, this topic will be discussed at length in Week 6 of our webinar.

In Conclusion

The take home message based upon data analysis is that the residents do not seem to be attending evening class because they prefer evening class. Residents seem to be attending evening classes mainly to attend classes instructed by Ms. Allbright. In fact, when *Class Instructor* is considered, *Class Assignment* is no longer significantly related to *Class Attendance.* It is also noteworthy that barriers to class did not impact *Class Attendance.*

The qualitative data also suggest that residents would in fact prefer to attend class in the morning. Therefore, moving classes to the evening (as administrators were considering) would be a mistake. Lastly, in response to our study research questions, the strongest predictor of the **Dependent Variable** *Class Attendance* is the **Independent Variable** *Class Instructor.*