Quantitative Data Analysis

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Essential Questions

1. How does one align a research study? What does this mean? What aspects of the study are aligned?
2. What is the purpose of collecting data for and presenting descriptive statistics for the study sample and for the variables?
3. Why is it important to compute scale reliability? What happens if a reliability coefficient is unacceptably low?
4. What is the purpose of statistical testing?
5. What is the difference between parametric and nonparametric tests? Which tests are preferred? What does one do if the assumptions for a parametric test are violated (not met)?

Introduction

Understanding, writing, and conducting data analysis can be challenging. Yet, it is essential for successful doctoral research. In Chapter 3 of the dissertation, the proposed data analysis plan is presented. Chapter 4 of the dissertation contains a concise summary of the study and includes the analyzed data, often presented in text, tabular, and/or figure format. Chapter 4 concludes with a thorough presentation of the study results. The following will demystify the process and provide tools to assist in formulating a quantitative data analysis plan.

Quantitative designs are classified as experimental and nonexperimental. Experimental designs include an intervention; nonexperimental designs are observational only. As a reminder, Grand Canyon Univrsity (GCU) has a set of core designs that are recommended for doctoral researchers. For quantitative studies, these designs include pre-experimental, quasi-experimental, correlational or associative, correlational–predictive, comparative, and ex post facto (see Table 4.1).

Table 4.1

Quantitative Core Designs and Descriptions

Design	Description
Pre-Experimental	Examines the effect/outcome of some form of treatment(s) using either one or two pre-existing group of participants. May use a one-shot comparison group (not a control group measured pre and post). *Uses primary data (i.e., data collected by the learner).*
Quasi-Experimental	Examines the effect/outcome of some form of treatment(s) using either one or two pre-existing group of participants. May use a control group measured pre and post. *Uses primary data (i.e., data collected by the learner).* Note: lack of random sampling is key in quasi-experimental designs, differentiating it from a true experimental study design where a random sampling is required.
Correlational or Associative	Examines relationship(s) between pairs of variables using data from a single group of participants with the intent of assessing the direction and strength of a relationship. *Can use primary (i.e., collected by the learner) and/or secondary data (i.e., not collected by the learner).*
Correlational-predictive	Examines relationship(s) between two or more variables using data from a single group of participants, with the intent of *predicting* a criterion variable from one or more predictor variables. *Can use primary (i.e., collected by the learner) and/or secondary data (i.e., not collected by the learner).*
Comparative	Examines differences between two or more groups defined by one or more categorical variables and/or between two or more measurements of a single group. *Uses primary data (i.e., collected by the learner) and there is no manipulation of variables.*
Ex Post Facto	Examines differences between two or more groups defined by one or more categorical variables and/or between two or more measurements of a single group. *Uses secondary data (i.e., not collected by the learner).*

Study Alignment

Study alignment is the quality of a research process when all elements, characteristics, and procedures support each other toward the end goal of addressing the problem statement. According to Creswell and Creswell (2017), this includes the "procedures of inquiry (called research designs); and specific research methods of data collection, analysis, and interpretation" (p. 50). To effectively align a study, more needs to be considered than just the problem statement. The title, academic need/gap/problem space, problem statement, purpose, variable structure, research questions, design, and statistical tests need to be considered and aligned. GCU uses specific formats for many of these items. Below is an example template of an aligned problem statement, purpose, and one research question.

Problem Statement: It is not known if and to what extent a relationship exists between [Variable A] and [Variable B] for the **target population**.

Purpose Statement: The purpose of this quantitative correlational study is to measure if and to what extent a relationship exists between [Variable A] and [Variable B] for the population in the location.

Problem and Purpose Statements

The problem statement

- is one sentence based on the arguments from the literature that present what needs to still be studied.
- should be phrased "it is not known if and to what extent" for quantitative studies and "It is not known how" for qualitative studies.

The purpose statement

- is a single sentence that connects several study components.
- should be formatted as follows: methodology + design + problem statement + target population + location.

RQ_1: If and to what extent does a relationship exist between [Variable A] and [Variable B] for the population?

$H1_0$: A statistically significant relationship does not exist between [Variable A] and [Variable B] for the population.

$H1_A$: A statistically significant relationship does exist [Variable A] and [Variable B] for the population.

Associated Words

In addition to making sure the exact same terms are used in the problem statement, purpose statement, and RQs, other terminology used throughout the dissertation must be aligned and consistent with the design choice. Some examples of words associated with specific quantitative designs are shown in Table 4.2. The alignment matrix is also a helpful tool to determine whether a study is in alignment (see Table 4.3).

Table 4.2

Examples of Words Associated with Specific Quantitative Designs

Design	Associated Words
Pre-Experimental	Pre/post, before/after
Quasi-Experimental	Difference
Correlational or Associative	Relationship, correlate, correlation
Correlational–Predictive	Predict
Comparative	Difference, between
Ex Post Facto	Difference (archived data), between

Table 4.3

Alignment Matrix

<table>
<tr><th colspan="3">Alignment Matrix</th></tr>
<tr><td colspan="3">Directions: Please complete the following fields with information about your study.</td></tr>
<tr><td colspan="3">Name:</td></tr>
<tr><td colspan="3">Date:</td></tr>
<tr><td colspan="3">Course:</td></tr>
<tr><td colspan="3">Title/Topic:</td></tr>
<tr><td>Problem Space/Gap – (Cut and paste the problem space/gap statement from your dissertation. Include the page number):</td><td>Problem – (Cut and paste the problem statement from your dissertation. Include the page number):</td><td>Purpose – (Cut and paste the purpose statement from your dissertation. Include the page number):</td></tr>
<tr><td colspan="3">Phenomena (Qualitative) / Variables (Quantitative) – (List the phenomena/variables for which you will collect data):</td></tr>
<tr><td colspan="3">Theories/Models – (List the theories or models from the “Chapter 2 Conceptual Framework” section):</td></tr>
<tr><td colspan="3">Research Questions – (Cut and paste the specific research questions that your study will address. Include the page number):</td></tr>
<tr><td colspan="3">Methodology and Research Design - (List the methodology and the design that you will use for your study. If the methodology and design are not yet determined, leave this section blank).</td></tr>
</table>

Example

Consider the following example for a research study:

- **Problem Space:** Future research could examine the correlation between doctoral student engagement and resiliency in an online program.
- **Problem Statement:** It is not known if and to what extent a relationship exists between student engagement and resiliency for doctoral learners in an online program.
- **Purpose Statement:** The purpose of this quantitative, correlational study is to measure if and to what extent a relationship exists between student engagement and resiliency for doctoral learners in an online program at a university in the Southwest United States.
- **Research Question:** If and to what extent does a relationship exist between student engagement and resiliency for doctoral learners in an online program?
- **H_{10}:** A statistically significant relationship does not exist between student engagement and resiliency for doctoral learners in an online program.
- **H_{1A}:** A statistically significant relationship does exist between student engagement and resiliency for doctoral learners in an online program.

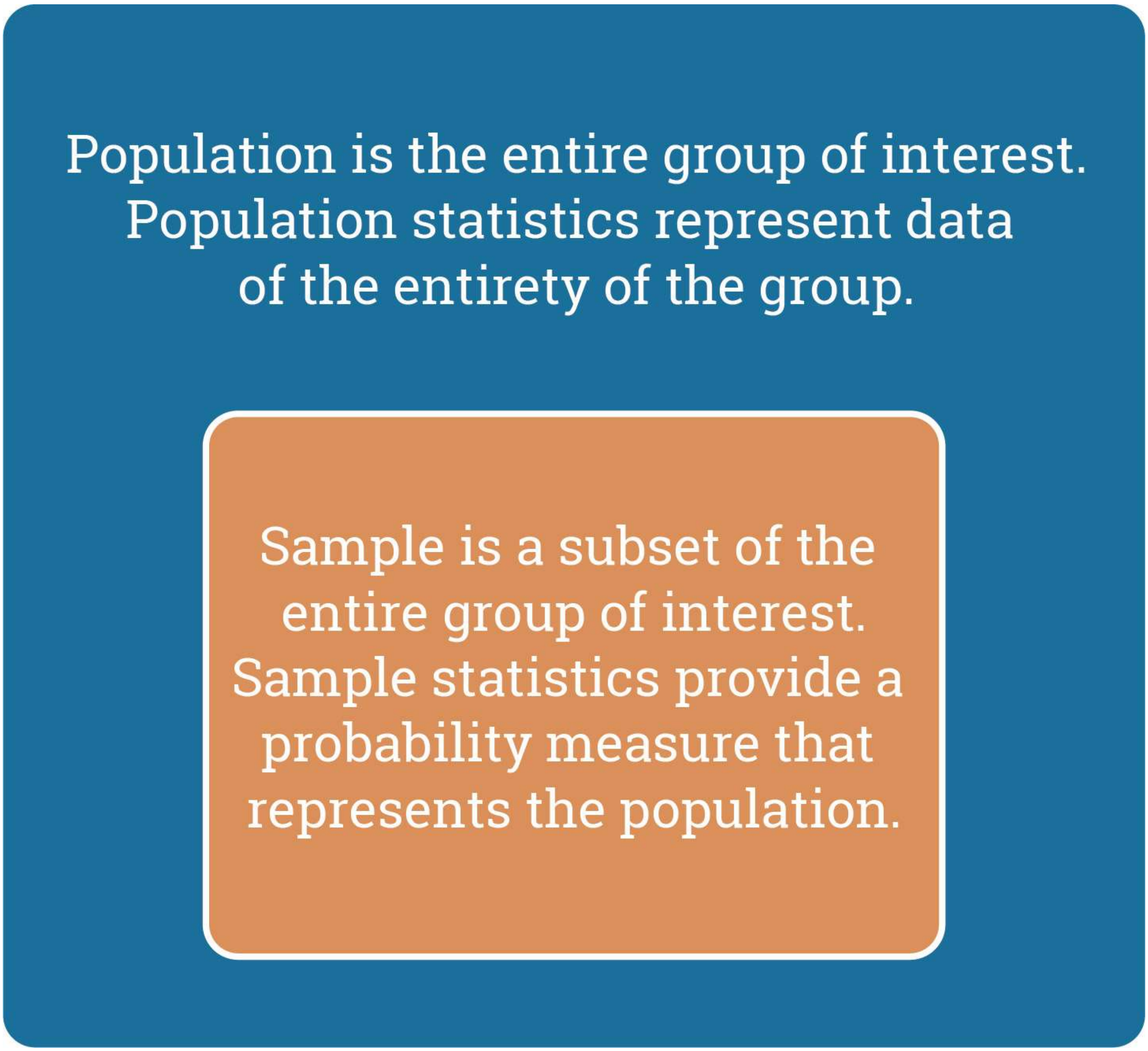
This example clearly demonstrates how the same wording is carried through from problem statement to purpose, RQs, and hypotheses. This can prove hard for more creative writers to accept, but do not change it. Keep it consistent. Some may call it boring; we call it alignment.

Inferential Statistics

While descriptive statistics describe the data, inferential statistics allow for inferences about the data. In research, data collected from a sample are evaluated or analyzed (see Figure 4.1). Using inferential statistics, the results from this sample can be generalized to a larger population (commonly referred to as the general population or simply, population).

Figure 4.1

Population v. Sample



Inferential statistics are based on probability theory; statistics are an approximation of reality (from a smaller sample to the larger population). For example, when one uses inferential statistics on a sample size of 97 in a correlational study to determine if a relationship exists between two variables and the results of the correlation are statistically significant, one can reasonably generalize these results from the sample to the target and general population, as well.

Inferential statistics provide a method for describing features of data and understanding relationships between concepts and, therefore, hypothesis testing. Examples of some inferential statistics include Pearson Correlation, ANOVA, and multiple linear regression. Appropriate nomenclature for the sample is n, while the number in the general population is N.

Scales of Measurement

One of the most important aspects to understand is the scale of measurement for each variable in a research study. Identifying the appropriate scale helps to determine what statistical analysis can be performed. Variables can be divided into two types: categorical and continuous. See Table 4.4 for a summary.

Categorical variables are those that are in "buckets" with labels or categories. Nominal and ordinal variables are both categorical. Nominal variables are those that consist of a set of categories that have different names. Measurements on a nominal scale label and categorize observations but do not make any quantitative distinctions between observations. Examples of nominal variables are teacher, principal, White, Hispanic, Black, etc. Ordinal variables consist of a set of categories that are organized in an ordered sequence. Measurements on an ordinal scale rank observations in terms of size or magnitude (Gravetter & Wallnau, 1996). Examples of ordinal variables include grade (freshman, sophomore, junior, senior) and Likert-scale items.

Continuous variables are those that are counted or measured. Interval and ratio variables are continuous. Interval variables consist of ordered categories that are all intervals of exactly the same size. Equal differences between numbers on a scale reflect equal differences in magnitude. However, the zero point on an interval scale is arbitrary and does not indicate a zero amount of the variable being measured. An example of this is Likert-scale means or sums. A ratio scale is an interval scale with the additional feature of an absolute zero point. With a ratio scale, ratios of numbers do reflect the magnitude (Gravetter & Wallnau, 1996). Examples include standardized test scores and height.

Table 4.4

Scales of Measurement

Categorical (Variables that take categories as their values)		Continuous (Variables that have values that represent a counted or measured quality)	
Nominal	**Ordinal**	**Interval**	**Ratio**
A nominal scale consists of a set of categories that have different names. Measurements on a nominal scale label and categorize observations but do not make any quantitative distinctions between observations (e.g., teacher, principal, White, Hispanic, Black, etc.).	An ordinal scale consists of a set of categories that are organized in an ordered sequence. Measurements on an ordinal scale rank observations in terms of size or magnitude (e.g., freshman, sophomore, junior, senior. Likert-scale items).	An interval scale consists of ordered categories that are all intervals of exactly the same size. Equal differences between numbers on a scale reflect equal differences in magnitude. However, the zero point on an interval scale is arbitrary and does not indicate a zero amount of the variable being measured (e.g., Likert-scale means or sums).	A ratio scale is an interval scale with the additional feature of an absolute zero point. With a ratio scale, ratios of numbers do reflect the magnitude (e.g., reading scores, height).

Note on Use of Likert Scales in Studies

If an instrument has a Likert scale, state that the technically ordinal scale was approximated to continuous (and classified in the data file as such). Although individual Likert-type items are ordinal, when they are aggregated by calculating a sum or a mean, for example, they are interval.

Make sure that this is justified with thought leaders or other studies using the instruments that do the same (not necessarily related to the study).

For an example of how this was done in a dissertation, see *Compassion Satisfaction, Burnout, Secondary Traumatic Stress, and Work Engagement in Police Officers* (Chiappo-West , 2017)

Something like this is needed: “All measurement instruments employed Likert-type items on either a 1–5 or 1–6 scale [insert actual values] and are described in detail in 'Instrumentation' in Chapter 3. Although individual items are, therefore, ordinal in nature, authors such as

Norman (2010) and Boone and Boone (2012) have provided evidence that Likert-style data in the aggregate (e.g., means and sums) can be treated as an interval measure for statistical purposes. All variables in this study were treated as interval data."

Variable Types

In addition to using terms that are consistent with methodology and design, researchers should also make sure to use the appropriate terminology when referring to variables. Correlational/association studies have variables. Predictive correlational studies have predictor and criterion variables. Comparison studies have independent variables and dependent variables. There are other types of variables that may come up as well in more complicated analyses, including confounding variables, mediation variables, and moderating variables. The common variable types are defined in Table 4.5.

Table 4.5

Variable Types

Design	Variable Type	Definition
Correlation/Association	Variable	**Variable:** A characteristic or condition that changes or has different values for different individuals (units of analysis).
Correlational–Predictive	Predictor/Criterion	**Predictor:** A variable in regression that is used as part of a model to predict an outcome. **Criterion:** A variable in regression that is the outcome of a model.
Comparison (pre-experimental, experimental, quasi-experimental, comparative, and ex post facto)	Independent Variable/Dependent Variable	**Independent:** A variable that is not changed by any other variable or factor. **Dependent:** A variable that is changed by another variable or factor.

Variable Structure

Identifying and defining the variables used in the study is done at the conceptual, operational, and measurement levels (see Table 4.6). The conceptual definition is what does it mean (with a citation). An operational level is how the researcher will measure the variable to reflect the conceptual definition. The measurement level in Table 4.6 is where one includes whether the variable is nominal, ordinal, interval, or ratio. Also, in the measurement level column, the variable type is identified. The last column includes the instrument or data source used to collect the data for that variable, again with a citation (see the example of alignment with data analysis at the end of this chapter).

Table 4.6

Variable Table

Variable	Conceptual Definition	Operational Definition	Measurement Level	Instrument/Data Source
[Variable 1]				
[Variable 2]				
[Add Variables as needed]				

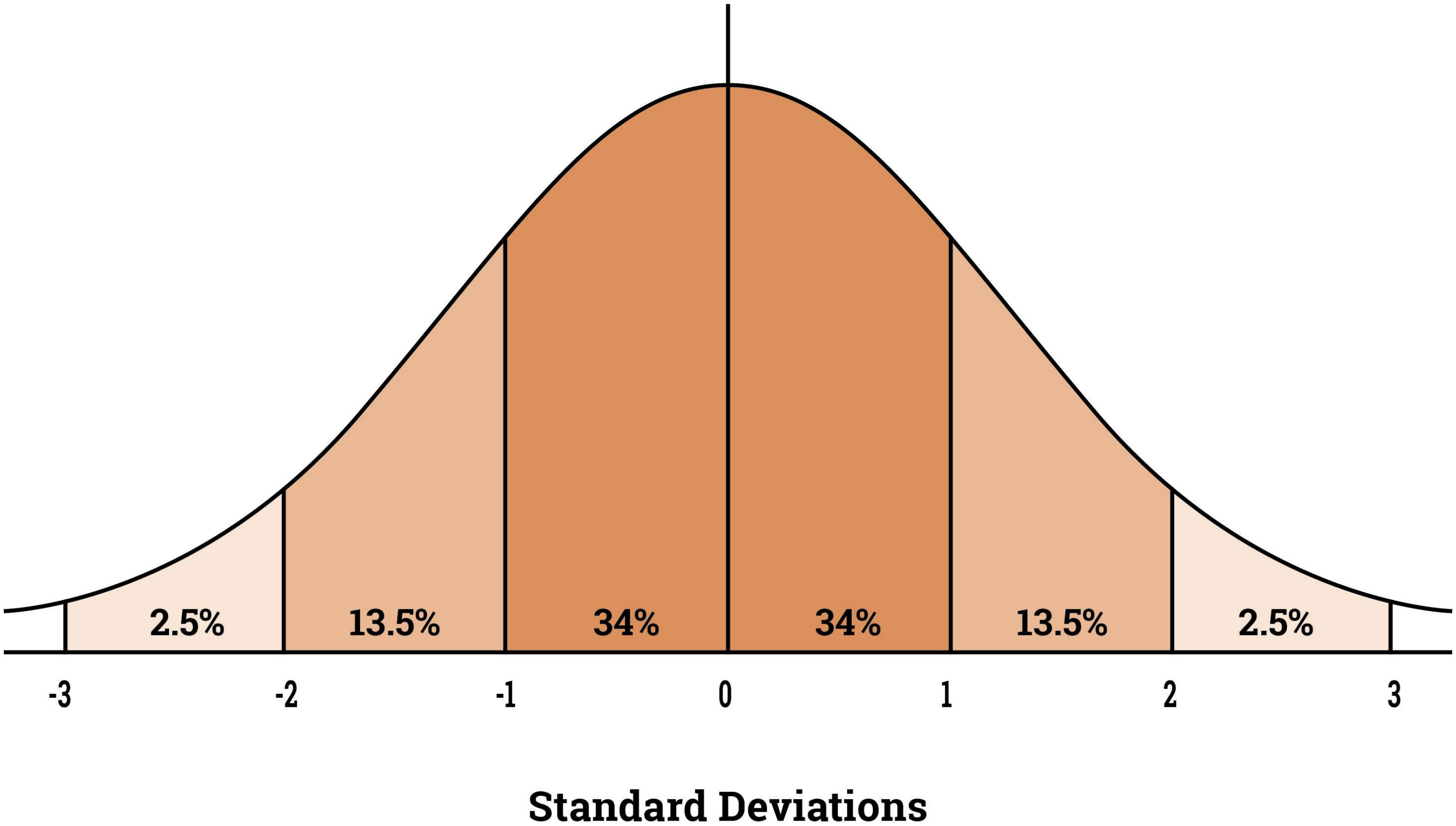
Parametric Versus Nonparametric Tests

Distribution patterns for data play a crucial role in the type of statistical analysis that can be conducted. Unfortunately, it is not known going into the study what the data will look like following data collection. Data distribution can be parametric or nonparametric.

Parametric, or normally distributed data, have a distribution in the shape of a bell curve and are perfectly symmetrical about the mean. With normally distributed data, the mean, median, and mode are all equal (see Figure 4.2). The x-axis indicates standard scores; standard scores indicates how many standard deviations a value is from the mean of the normal distribution. Thus, a standard score of +1 is one standard deviation above the mean, and a standard score of -1 is one standard deviation below the mean. The percentages tell the percent that are expected between the mean and a particular standard score if the data were normally (parametrically) distributed (Nelson, 2020).

Figure 4.2

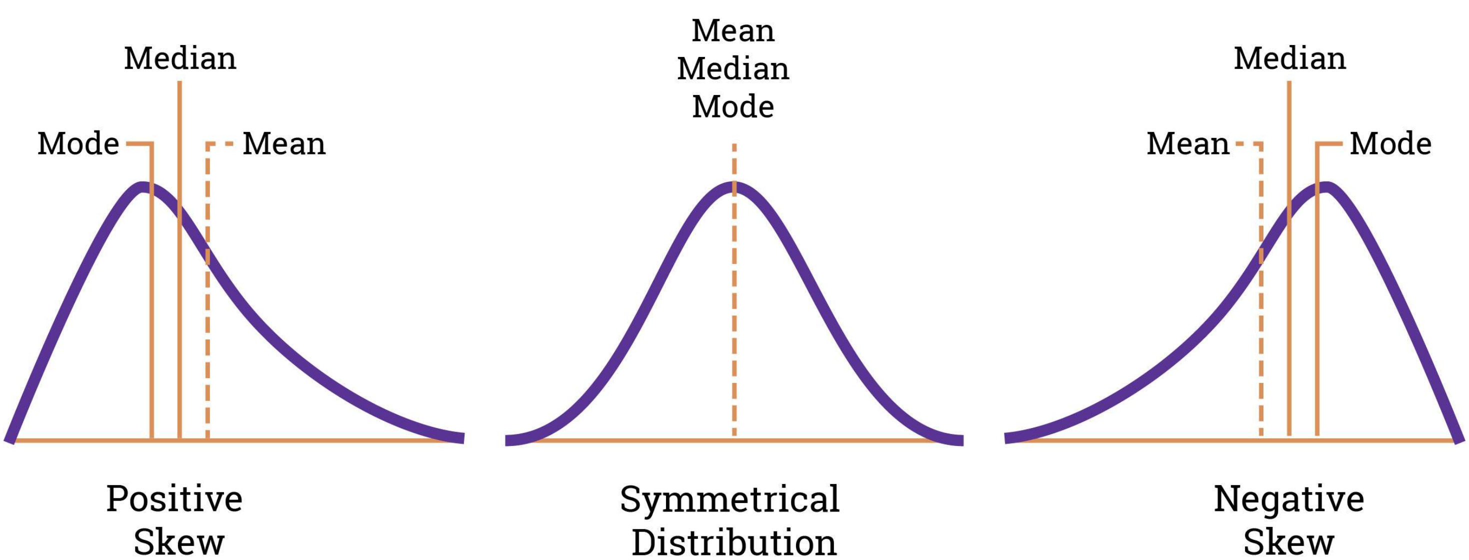
Normal Distribution/Gaussian Curve



Skewness measures the symmetry of the data distribution. A skewness coefficient equal to zero indicates a perfectly symmetric distribution (as in normally distributed data). A good way to think of skewness is the "tail" of the curve. If the tail is to the left, then it is called a negatively skewed distribution. If the tail is to the right, then it is called a positively skewed distribution (see Figure 4.3) (Nelson, 2020). When data are heavily skewed, they are nonparametric or non-normally distributed. In these cases, many inferential statistics are not valid, and, therefore, an alternative statistical analysis approach should be considered. This is further discussed in the "Assumptions" section.

Figure 4.3

Positive, Symmetrical, and Negatively Skewed Data



Determining the Appropriate Inferential Statistic

Recommended designs are associated with specific statistical analyses (see Table 4.7). Just like the problem space/need, problem statement, purpose statement, and RQs need to be in alignment, so do the design and data analysis.

Quantitative designs can be thought of as falling into two groups: correlations and comparisons. Correlations will use Pearson (correlation), linear regression (prediction with one predictor and one criterion), or multiple linear regression (prediction correlation with more than one predictor). A problem statement with a correlation would be stated as "It is not known if and to what extent a relationship exists between student engagement and resiliency for doctoral learners in an online program." If stated as a predictive correlation, the problem statement would read "It is not known if and to what extent student engagement predicts resiliency for doctoral learners in an online program."

Comparison with two groups uses a *t* test, and a comparison with more than two groups will use ANOVA. An example of a problem statement with two groups (that would use a *t* test) is "It is not known if and to what extent a difference exists in student engagement between online doctoral learners with high or low resiliency." In this case, there are two groups: high and low resiliency (with cutoffs determined from peer-reviewed literature). By contrast, if there were more than three groups (that would use ANOVA), the problem statement may read "It is not known if and to what extent a difference exists in student engagement between online doctoral learners with high, medium, or low resiliency."

While these examples are simplifications, and there can be special considerations within each inferential statistic, they are a useful guide. Table 4.7 helps to determine which test to use according to design. Laerd.com also provides a "Statistical Test Selector" that walks through a series of questions to assist in selecting the best inferential statistic for the study.

Table 4.7

Identification of Inferential Statistics Usually Used with Each Design

Design	**Inferential Statistic**
Pre-Experimental	*t*-test or ANOVA
Quasi-Experimental	*t*-test or ANOVA
Correlational or Associative	Pearson correlation
Correlational–Predictive	Linear or multiple regression
Comparative	*t*-test or ANOVA
Ex Post Facto	*t*-test or ANOVA

Many learners use Laerd.com for determining the proper statistical analysis and learning the chronological steps needed to complete that analysis. Laerd.com has a statistical test selection tool that is helpful in deciding what is appropriate for a study. The site also has useful guides that provide an overview of statistics, identify assumptions, offer step-by-step directions for how to do each test in SPSS, and describe how to interpret and report the result in APA format. Visit the DC network for a discount code (under the “Software” tab on the left on the home screen; then “Laerd” and scroll to the bottom).

Data Analysis Steps

Data analysis includes multiple steps: cleaning and compiling the data, descriptive statistics, identifying the appropriate inferential statistic to test each set of hypotheses, assumption testing, interpretation, and post hoc analyses. In addition to a detailed description of how the data will be analyzed, a rationale for the data analysis approach (again, from peer-reviewed literature) for the study must also be included. A high level overview of the data anlysis steps are presented here.

Cleaning and Compiling the Data

Cleaning and compiling the data includes several steps. Once data collection is finalized, the data are downloaded into statistical software, typically SPSS. The data are reviewed, and any outliers are removed. Missing data are reconciled or deleted. Methods for detailing with outliers and missing data will be clearly outlined in the proposal.

Descriptive Statistics

Demographic information and variables for a study are presented using descriptive statistics. Descriptive statistics can include measures of central tendency such as mean, mode, median, standard deviation (stddev), standard error (stderr), z-skewness, and z-kurtosis for continuous variables. For categorical variables, this includes frequencies or proportions.

Scale reliability coefficients (Cronbach’s alpha) are calculated for all variables/instruments used in a study. This confirms that the instrument is reliable for measuring each variable. Reliability coefficients should be computed on the study variables and compared with reliability coefficients as reported by instrument authors and prior users. Low reliability (< 0.7) may require changes in the data analysis approach (i.e. dropping variables with unreliable data).

Inferential Statistical Analysis Identification

A specific statistical analysis approach is identified for each set of hypotheses (e.g., Pearson R, multiple regression analysis, ANOVA). The approach is not just identified but also justified as to why the selected statistical analysis approach(es)/tests are appropriate with citations from peer-reviewed literature. Each identified statistical analysis should also include a literature-supported rationale.

Assumption Testing

Assumptions are a set of rules that must be met for the inferential statistic to be valid. Each inferential statistic has its own set of assumptions. These do not need to be memorized; they can always be looked up. Laerd.com serves as a strong tool for understanding assumptions. For each selected statistical test, learners must identify the specific set of assumptions to be tested and then describe how each assumption will be tested.

If the assumption is not met (violated), then alternative statistical analyses need to be considered. Parametric (normality) data assumptions often are violated. When this happens, alternative analyses will need to be conducted. Options for alternative analyses include accepting or ignoring the violation, transforming the data, or using the nonparametric alternative inferential statistic.

The most frequently violated assumption is normality. In that case, the nonparametric equivalent would be used. Below are the parametric and nonparametric equivalents of some standard statistical analyses used in GCU dissertation research:

- Pearson correlation (normally distributed); Spearman correlation (not normally distributed)
- Independent t test (normally distributed); Mann-Whitney (not normally distributed)
- Paired-sample/Dependent *t* test (normally distributed); Wilcoxon (not normally distributed).

Hypotheses Testing and Interpretation

Once assumption testing has is completed and a plan of action determined, the planned statistical analysis can be done. Remember, an inferential statistic is needed to test each set of hypotheses (null and alternative). Keep in mind the Type I error rate (alpha) that was used in calculating the sample size; this will be used for interpreting the data produced from the statistical analysis. If the result is statistically significant, the null hypothesis is rejected. If the result is not statistically significant, the null hypothesis fails to be rejected.

Consider correcting for experimental-wise Type I error rate using a Bonferroni correction if the same variable is used in more than one RQ with a Pearson correlation analysis.

Post Hoc Analysis

Post hoc analysis is performed to determine the actual power achieved in a study. Completing a post hoc analysis is required in two scenarios. The first is if the actual sample is smaller than the desired sample size, as determined by a priori G-power. The second scenario is if the null hypothesis fails to be rejected (in other words if statistical significance is not attained). Post hoc analysis is performed in G-power using the actual sample and calculated effect size. The post hoc analysis is included in the dissertation with the G-power calculation image included in the appendices. Further, the consequences (e.g., limitations, change of statistical analysis procedures, possibly even change of design) must also be considered and discussed within the dissertation.

Summary

In the proposal, the proposed data analysis plan is detailed. In the final dissertation, the data analysis and results are presented. Any changes done to data analysis following the proposal approval are presented in Chapter 4 of the dissertation. In Chapter 3 of the dissertation, the planned approach is presented; in Chapter 4, the actual approach is provided.

In Chapter 4 of the dissertation, the data analysis is presented just as it was outlined in Chapter 3. If the normality assumption is not met for a parametric analysis, the nonparametric equivalent is used. When this happens, the original assumptions are included in the data analysis section. The decision to switch to the nonparametric statistic is then discussed and justified, and further analysis proceeds, starting with assumption testing (as applicable) for the nonparametric statistic.

Example of Alignment with Data Analysis

- **Problem Statement:** It is not known if and to what extent a relationship exists between student engagement and resiliency for doctoral learners in an online program.
- **Purpose Statement:** The purpose of this quantitative, correlational study is to measure if and to what extent a relationship exists between student engagement and resiliency for doctoral learners in an online program at a university in the Southwest United States.
- **Research Question:** If and to what extent does a relationship exist between student engagement and resiliency for doctoral learners in an online program?
- **Variables:** See Table 4.8.
- **H_{10}:** A statistically significant relationship does not exist between student engagement and resiliency for doctoral learners in an online program.
- **H_{1A}:** A statistically significant relationship does exist between student engagement and resiliency for doctoral learners in an online program.

Table 4.8

Variable Table

Variable	Conceptual Definition	Operational Definition	Measurement Level	Instrument/Data Source
Student Engagement	Student's sense of control, intrinsic motivation, and future aspirations (Appleton et al., 2006)	Measured using the composite score; questions 1–35	Ordinal approximated to continuous; Likert 1–5	The Student Engagement Instrument (SEI) (Appleton et al., 2006)
Resiliency	The ability to cope with stress effectively (Organization Health, 2007)	Measured using the composite score; questions 1–35	Ordinal approximated to continuous; Likert 1–5	Resilience Assessment Questionnaire (RAQ) (Organization Health, 2007)

Example of Data Analysis Writeup

Cleaning and Compiling the Data

Before conducting any statistical analysis, the data are cleaned and compiled. Data will be downloaded from SurveyMonkey into SPSS to evaluate for completeness. Any incomplete responses will be deleted from further analysis. All data will be de-identified and codes will be assigned. Any reverse coded questions in the instrument will be notated in SPSS to ensure proper computations.

Descriptive Statistics

After preparation and cleaning, the final data set is ready for statistical analysis. First, descriptive statistics will be run on all demographics and variables. Descriptive statistics to include mean, median, standard deviation, standard error, skewness, and kurtosis will be provided for each all demographics and each variable. Scale reliability will be calculated by determining the Cronbach's alpha for each of the instruments (student engagement and resiliency).

Assumption Testing

The analysis used to evaluate RQ1 is Pearson correlation. There are five assumptions for Pearson correlation (Laerd Statistics, 2018). Again, these assumptions must be checked to make sure the data can be analyzed using Pearson correlation. It is only appropriate to use this statistical analysis if the data passes the five assumptions. The assumptions are:

1. Two continuous variables are measured at the interval or ratio level. This is determined as part of the scale measurement in designing the study.
2. The two continuous variables are paired so that each participant has one value for each variable.

3. A linear relationship must exist between the two variables. This can be tested through visual inspection of a scatterplot.
4. No significant outliers can be present. This is tested through visual inspection of scatterplots of all variables or box and whisker plots.
5. Assumption of bivariate normality. This is evaluated through tests for normality, including Shapiro-Wilks, Q-Q plots, or visual inspection of a histogram.

If all assumptions are met, then the statistical analysis will proceed as planned using Pearson correlation. If the assumptions are violated (not met), then Spearman correlation will be used.

Hypotheses Testing, Interpretation, and Post Hoc Analysis

Statistical significance for this study must reach $p \leq 0.05$. If this level of statistical significance is met, then the null hypotheses will be rejected in favor of the alternative. If statistical significance is not met, then the null hypotheses will fail to be rejected. Post hoc power analysis will be performed if minimum sample size requirements are not met or if the null hypothesis fails to be rejected,

Useful Quantitative Resources

In addition to the GCU textbooks (which are great resources for learning but should not be cited in your dissertation), the following resources are useful:

- Allison, P. D. (1998). *Multiple regression: A primer*. Pine Forge Press.
- Campbell, D. T., & Stanley, J. C. (1966). *Experimental and quasi-experimental designs for research*. Houghton Mifflin.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge.
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2002). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Routledge.
- Cooper, D. R., & Schindler, P. S. (2002). *Business research methods* (8th ed.). McGraw-Hill.
- DeVellis, R. F. (2012). *Scale development: Theory and applications*. SAGE.
- Field, A. (2013). *Discovering statistics using IBM SPSS statistics* (4th ed.) SAGE.
- Grimm, L. G., & Yarnold, P. R. (Eds.). (1995). *Reading and understanding multivariate statistics*. American Psychological Association.
- Keith, T. Z. (2015). *Multiple regression and beyond: An introduction to multiple regression and structural equation modeling* (2nd ed.). Routledge.
- Pelosi, M. K., Sandifer, T. M., & Sekaran, U. (2001). *Research and evaluation for business*. John Wiley.
- Shadish, W., Cook, T., & Campbell, D. (2001). *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin.
- Stephens, L. J. (2004). *Advanced statistics demystified*. McGraw-Hill.
- Tabachnick, B. G., & Fidell, L. S. (2012). *Using multivariate statistics* (6th ed.) Pearson.
- Warner, R. M. (2012). *Applied statistics: From bivariate through multivariate techniques*. SAGE.

Check for Understanding

1. Why do you use inferential statistics in your data analysis?
2. What is the difference between descriptive and inferential statistics?
3. What is assumption testing?
4. What happens if a reliability coefficient is unacceptably low?

Answers

completed.

4. Low reliability (alpha < 0.7) may require changes in the data analysis approach. This may include dropping variables with unreliable data from the analysis.

1. Inferential statistics are used in quantitative analysis when you want to infer properties of a sample to a larger population.
2. Descriptive statistics are used to summarize characteristics of data using central tendency and frequencies, for example. Inferential statistics allows for hypothesis testing that can then, using the probability theory, be generalized to a larger population.
3. Assumption testing is a process in which a set of rules for an inferential statistic are tested. These rules, or assumptions, must be met in order for the inferential statistical analysis to be valid. Assumption testing is done before any actual statistical analysis is completed.

References

Appleton, J., Christenson, S. L., Kim, D., & Reschly, A. (2006). Measuring cognitive and psychological engagement: Validation of the Student Engagement Instrument. *Journal of School Psychology, 44*, 427–445.

Boone, H. N., & Boone, D. A. (2012). Analyzing Likert data. *Journal of Extension, 50*(2). https://www.joe.org/joe/2012april/tt2.php

Chiappo-West, G. (2017). *Compassion satisfaction, burnout, secondary traumatic stress, and work engagement in police officers* (Publication No. 10607815) [Doctoral dissertation, Grand Canyon University]. ProQuest Dissertations & Theses.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches.* SAGE.

Gravetter, F. J., & Wallnau, L. B. (1996). *Statistics for the behavioral sciences:*

A first course for students of psychology and education (4th ed.). West Publishing.

Laerd Statistics. (2018). *Pearson's product-moment correlation using SPSS statistics. Statistical tutorials and software guides*. https://statistics.laerd.com

Nelson, E. (2020). STAT3S: Exercise using SPSS to explore measures of skewness and kurtosis. *Social Science Research & Instructional Center*. https://ssric.org/node/495

Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. *Advances in Health Sciences Education, 15*(5),625–632.

Organization Health. (2007). Resilience assessment questionnaire. *Organization Health Psychologist*. http://www.orghealth.co.uploads/PDFs/Resilience%20Assessment%20Questionnaire.pdf