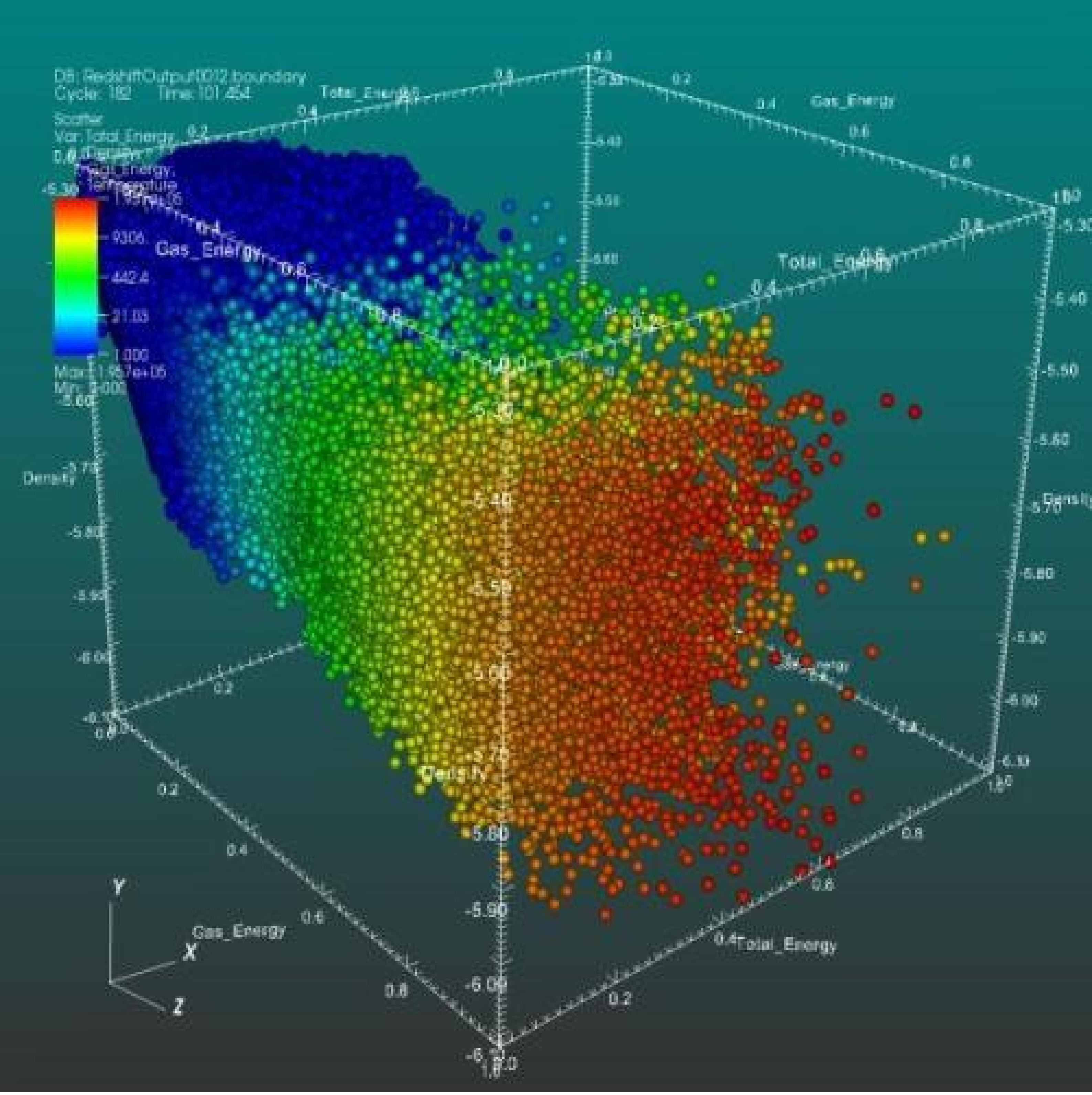

An Introduction to Quantitative Research Methods

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1

Introduction

When you have finished this book, you should be able to:

- Select a research topic that suits a quantitative methodology
- Write a research question
- Write a testable hypothesis
- Design and plan a quantitaive research project
- Demonstrate validity and reliability in your data collection methods.

My approach

My purpose is to make this topic as easy for you to learn as I can. I think of it as mostly a step-by step procedure, although many steps require you to make decisions.

Most full-length texts don't actually explain much. They tend to use complex language and often don't give definitions or examples, or make them so abstract that readers might not get the point. I've tried to remedy that. However, the topic actually becomes quite complex, so you might often need to go to more expansive textbooks.

If you are doing research for a degree, you should also ask for help. Most students are *not* experts in statistics so it's a good idea to work with a supervisor when:

- Designing complex experimental protocols or large-scale surveys.
- Using unfamiliar software.
- Performing advanced statistical analyses.
- Interpreting ambiguous or contradictory results.

Pre-requisites

I assume that you are already familiar with the research cycle and the conventions of research writing.

The jargon

The terminology is unavoidable. When I introduce a new term, I usually put it in a box like this:

Hypothesis
An hypothesis is a statement. It is not yet known whether or not it is true, but it can be tested to find out if it is true or not.

2

What is quantitative research?

Quantitative research uses statistical methods to analyze data and reach conclusions. More specifically, it is a systematic investigation of phenomena by gathering quantifiable data and performing statistical, mathematical, or computational techniques. It is a cornerstone of scientific research, providing evidence-based insights through rigorous, objective analysis.

How is *quantitative* research different from *qualitative* research?

Quantitative research emphasizes numerical data, which focuses on measurement, such as quantities, frequencies, or rates, and employs statistical tools to analyze this data. It uses standardized methods to ensure reliability and to enable other researchers to repeat methods. Tools are structured, and are designed to collect consistent, unbiased data. Examples include surveys, experiments, and structured observations

Qualitative research is quite different. It uses non-numerical data that focuses on themes, narratives, and descriptions in order to understand meanings, perceptions, or behaviors. The data is subjective and contextual, emphasizing individual experiences and the context in which they occur. Qualitative methodologies include as interviews, focus groups, and ethnographic studies, allowing for deeper exploration of complex topics.

Reliability
Results are consistent across items within a test, and over time for test and retest. Inother words, does it work the same way every time to give consistent results?

Validity
This term has two meanings:

1. *Internal Validity*: Ensures the study accurately measures the intended effect, free from confounding variables.
2. *External Validity:* Indicates how well results generalize to other populations or contexts.

Valid
A data-gathering method is valid when it measures what it is intended to measure.

The purposes of quantitative research

Quantitative research serves several purposes:

1. It measures variables by capturing numerical data to describe phenomena, such as demographics, market trends, or experimental outcomes.
2. It tests hypotheses. It evaluates theories or assumptions through statistical testing.
3. It Identifies relationships by analyzing correlations or causal links between variables to uncover underlying patterns.
4. It predicts outcomes. It uses models and algorithms to forecast future trends based on existing data.

When to use quantitative research

- When seeking numerical evidence to support conclusions.
- For large-scale studies requiring generalizability.
- To compare differences or changes across groups or over time.

Generalizability

A research result is generalizatble if it applies equally well to the members of the population outside the sample.

Weaknesses and limitations of quantitative research

Weaknesses and limitations are different. Weaknesses represent the potential for error, while limitations are restrictions to what it can do. Be careful not to overgeneralize; they do not necessarily apply to all quantitative researches.

The main weaknesses and limitations of quantitative research fit roughly into three categories, although some aspects relate to multiple categories.

Intrinsic limitations and weaknesses

Some limitations and weaknesses are intrinsic to the methodology itself.

1. Quantitative methods depend on qualitative data to generate and justify quantitative research questions and instruments.
2. Some studies need a huge number of participants to produce valid results, and getting good data can be time-consuming, difficult, and expensive. This is especially true for large-scale studies that require large sample sizes, and even more so when tests must be done individually in person, such as some medical studies. On the other hand, however, electronic distribution of surveys is often very, easy, fast, and cheap although respondents might return questionnaires late or not at all.
3. Quantitative methods can be reductionist; they oversimplify complex phenomena by reducing them to simple numerical values. Consequently they risk missing important nuances and variability., leading to an incomplete or inaccurate picture of the subject being studied.
4. They require significant statistical knowledge to interpret results, which can be challenging for researchers without strong statistical backgrounds.
5. Quantitative research methods are often rigid and inflexible, making it difficult to adapt to unforeseen issues or changing circumstances.

6. The predetemined approach makes it difficult to adapt to new findings or changes in the research environment.
7. If research depends on a historical dataset, the dataset must be large enough to justify subsequent conclusions.
8. Results and findings are limited to the narrow focus of the research. For example, narrowly-focussed, rigidly structured questionnaires result in narrowly focussed data, resulting in narrowly focussed results and findings. Closed questions in questionnaires with a given small set of responses can restrict participants' freedom to express their thoughts and opinions.
9. The data must be tidied up so that it fits the researcher’s categories (called “over-fitting”, risking significact changes in the data before it is measured. This espeically applies to the removal of ambiguity so that data items clearly fit in one or another category. Good testing of tools and cross-validation do not fully overcome the risk of overfitting.
10. It is probablistic. It only indicate what is probably so, and can seldom produce confirmed conclusions. While it might identify relationships, it is has difficulty confirming them.
11. It tends to follow the majority and ignore *outliers*. Some statistical procedures can simply ignore them. However, outliers can be important in other circumstances, for example, a medicine that kills a small percentage of patients.

Outliers
An outlier is a data item that is outside the general pattern or trend of the data.

High risk of error

Despite the increased risk of error compared to qualitative reseerch, quantitative researchers have various methods to suppress most of the risks they face. As you progress through this book, you’ll learn to mitigate each of these risks.

1. Bias compromises the integrity of much research.
    a. Confirmation bias compromises the integrity of much research. Researchers unconsciously seek data that will confirm their preconceived ideas.
    b. Researchers can manipulate data or statistical tests to achieve desired outcomes (called “p-hacking”).
    c. Despite the assumption that quantitative researchers can remain completely objective and detached, they can be biased in data collection, measurement, and data interpretation, leading to incorrect results. The final report can conceal bias by appearing to be objective. In particular, data collection methods like surveys can include leading questions or have limited response options.
    d. The purpose of many models is to explain the relationship between different variables. They have parameters that researchers can tweak to optimize the results.

2. The margin of error assumes that respondents were randomly selected from the population, and that every respondent answered honestly. However, these assumptions are never true in real research.[1]
3. Statistical data and analysis methods can be complex. Analysis often requires advanced statistical knowledge, which is a barrier for some researchers. Consequently, they risk misinterpretation of statistical results, such as confusing correlation with causation. This can lead to incorrect conclusions about the relationships between variables. It can be especially difficult to link statistical analysis to findings that address the research question.
4. If the sample does not represent the population, the results may not be generalizable. While larger sample sizes can improve reliability, biased sampling methods can result in samples that do not represent the broader population.
5. It can be difficult to ensure that data is accurate, complete, and consistent.
6. Flawed instruments can lead to incorrect conclusions. The accuracy of research results depends on the validity and reliability of the instruments used in collecting data, for example, surveys and tests.
7. Researchers might fail to identity unanticipated factors or variables (called confounding variables) that could influence the research outcomes.
8. Circular logic sometimes poses a peculiar problem. It is easy for researchers to magically transform unconfirmed assumptions into confirmed conclusions, even when they are not actually tested in the research.

When not to use quantitative research

- When exploring new or poorly understood phenomena, especially where context is critical.
- For studies requiring nuanced, in-depth understanding of subjective experiences.
- For studies dealing with subjective experiences or interpretations.
- When the study explores underlying meanings.
- The topic focuses on understanding complex processes.

Quantitative methods do not have the explanatory power of qualitative research research. Here’s why:

1. They often fail to explain “why” and “how” and can only show “what” and “to what extent.”
2. The rigidity of predetermined variables and questions prevents or limits the exploration of unexpected results, insights, or dynamics of change, especially in social contexts where qualitative factors play a significant role.
3. Quantitative methods do not allow for the discovery and exploration of new ideas or unexpected patterns, themes or insights that emerge during data collection. However, some kinds of analytical software can identify patterns in data that are imperceptible to humans.
4. They overlook the effects of context on data. When researchers create controlled environments, they might not reflect real-world situations and might have limited ability

[1] With thanks to Kenton Mαchinα, UCLA.

to understand the context of the data. This can lead to a lack of understanding of the underlying reasons for certain behaviors or trends

5. They cannot explore subjective experiences and deeper, more nuanced meanings behind behaviors, motivations, experiences, feelings, opinions and perceptions, especially those of the individual. They might not capture subtle complexities of social interactions. This is a result of prioritizing the researcher's perspective over that of participants.
6. They have difficulty capturing the dynamics of change over time, especially in social contexts where qualitative factors play a significant role.

Is your topic suitable for quantitative research?

You can determine whether a topic is suitable for quantitative research by evaluating several key factors. By aligning the research topic with these factors, you can confidently determine its suitability for quantitative research.

Here's a breakdown of considerations:

1. *Nature of the research question*. Quantitative research is appropriate for questions that seek to measure, quantify, or evaluate phenomena.
   a. Suitable research questions often start with words like:
      i. How much ...?
      ii. To what extent ...?
      iii. What is the relationship between ...?
      iv. What are the effects of ...?

   Examples:
   - "What is the average income of individuals in a specific region?"
   - "To what extent does exercise impact mental health?"
2. *Availability of measurable variables*. Quantitative research requires the topic to involve variables that can be objectively measured or quantified. Variables might include:
   a. Nmerical data (e.g., age, income, test scores)
   b. Categorical data (e.g., gender, education level, job type)
3. *Need for statistical analysis.* Quantitative research is ideal when the goal is to analyze data statistically to identify patterns, trends, relationships, or causation. For example, you might ask whether education level correlates to income.
4. *Generalizability*. Use a quantitative approach if the research aims to generalize findings to a larger population. Quantitative methods often involve larger sample sizes and structured data collection, making generalization feasible.
5. *Structured collection of statistical data*. Quantitative research uses instruments such as surveys with closed questions, experiments, and standardized tests. However, if the topic involves flexible or evolving data collection, qualitative methods may be more appropriate.
6. *Pre-existing theories or frameworks*. Quantitative research often tests hypotheses or theories. If a clear theoretical framework exists, the topic may lend itself to quantitative methods, for example, testing a hypothesis about the impact of a new teaching method on student performance.

7. *Research goals*. The topic is probably suitable for quantitative research if the purpose is to determine cause-and-effect relationships, measure prevalence or incidence, compare groups, or to validate or test instruments.
8. *Feasibility*. Ensure the topic is feasible for quantitative research in terms of availability of data, access to participants, resources for statistical analysis, and ethical considerations.

3

Types of Statistics

Descriptive Statistics

Descriptive statistics is a set of methods to summarize and organize raw data into understandable formats. Key techniques include:

Measures of central tendency:

- *Mean*: The average value, useful for normally distributed data.
- *Median*: The middle value between the highest and lowest. It is not affected by outliers and skewed data.
- *Mode*: The most frequently occurring value, suitable for categorical data.

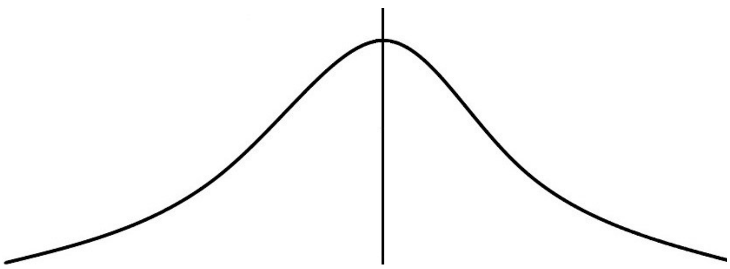
Measures of variability:

- *Range*: The difference between the highest and lowest values.
- *Variance*: The average squared deviation from the mean, measuring dispersion.
- *Standard deviation*: The square root of variance, representing the typical spread of data.
- *Skewness*: The extent to which values are not centered at the mean.

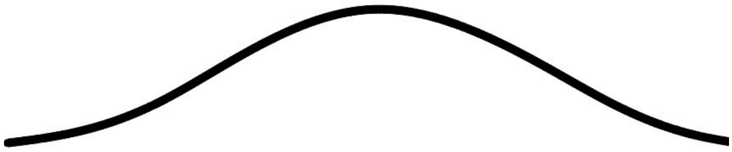
The difference between ***variance*** and ***standard deviation***

Variance and standard deviation are two different ways of measuring dispersion or variance, and they are calculated in different ways. While both provide information about dispersion, the standard deviation is often preferred because it is easier to interpret and more practical for many analyses, especially when looking at relative differences. Variance is more useful in some theoretical contexts, such as in statistical modeling or analysis.

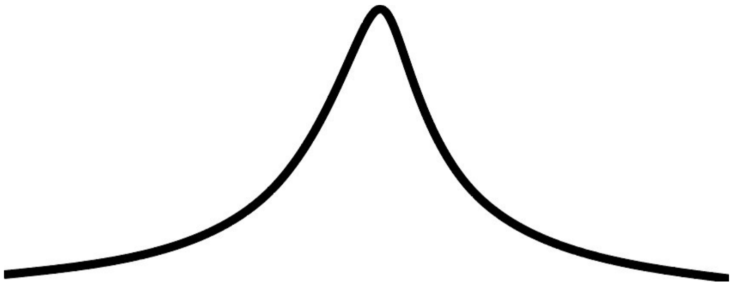
Normal distribution with values centered at the mean



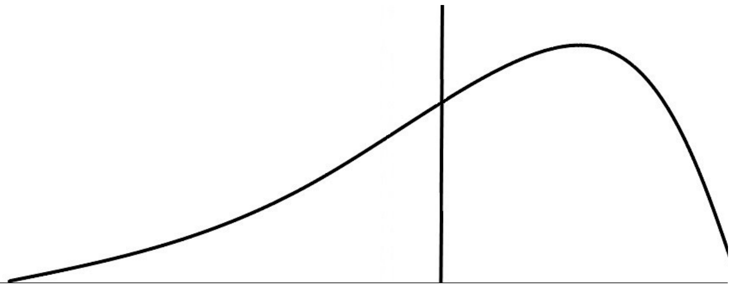
Normal distribution with high dispersion



Normal distribution with low dispersion



Skewed distribution



Inferential Statistics

Inferential statistics allow researchers to generalize findings from a sample to the broader population. Common methods include:

- Hypothesis testing such as T-tests, which compare means between groups, and (Analysis of Variance (ANOVA), which analyzes differences among multiple groups.
- Estimating population parameters:
- Use confidence intervals to provide a range of likely values for population characteristics.

Confidence level **and** ***Confidence interval***

The *confidence level* is the percentage of times expected to get close to the same estimate if the experiment is run again again or the population is resampled in the same way.

The *confidence interval* is the upper and lower bounds of the estimate expected at a given confidence level.

4

About experimental research

The basic idea of experiments is that if one compares two things that are equal in all other ways, then the difference represents new knowledge. For example:

> The teacher put two identical seeds in two identical pads of cotton wool. The students watered only one seed, then the class observed the difference. Only the seed with water germinated. The students then concluded that seeds need water to germinate.

> The action is the *treatment*.
> The group that gets the treatment is the *treatment group.*
> The group without the treatment is the *control group*.

Non-designs

When It's Not Experimental Research

Some data collection methods are not experimental research. Descriptions and surveys are not experimental designs. The researcher surveys the sample to get information about them. The data might be quite accurate, but the researcher has not compared the results with any other group. Consequently, the researcher has no reason to conclude that anything in the group is different from any other similar group.[2]

In quantitative research, descriptions and surveys are primarily used for data collection, but whether they are considered research methods depends on how they are used within the research design. It is not research simply to gather and present raw data. Collecting data survey but only presenting raw data without analyzing patterns, , or trends means you have data collection but not actual research.

If the goal is to summarize or describe a phenomenon or the characteristics of a sample in detail, then the description itself can be part of a broader research method, particularly in descriptive research designs. This can include mapping trends, patterns, or demographics, which are used to answer research questions. Some description and survey data can be analyzed to evaluate programs and methods.

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[2] Tuckman, Bruce W. 1978, *Conducting Educational Research.* Second ed. (New York: Harcourt, Brace Jovanoch0 p. 9.

One-shot Case Study

The researcher applies the treatment to a single group and then assesses its effect. This is also not experimental design, because it does not compare anything. One cannot know whether the treatment had any effect at all, or whether the treatment caused the effects, because other factors might have been the cause. For example, the change might have happened anyway due to maturation of the people in the group.[3]

One group Pre-test/post-test

The researcher tests something in a single group (the pre-test), apply the treatment to the group, and then give another test (the post-test). The researcher then compares the pre- and post-test results to find out what effect the treatment had. However the reseaercher cannot know what precisely caused the change, and changes might have happened anyway due to maturation of the people in the group. It is another kind of non-design.[4]

Intact Group Comparison

The researcher divides the subjects into two groups, applies the treatment to only one group, and compares the effects on both groups. However, the group members are not necessarily equivalent, (e.g. not randomly chosen), so the researcher has no way to know whether or not the treatment caused the results. It is another kind of non-design.[5]

Real Experiments

Post-test Only Control Group

The researcher divides subjects into two randomly chosen groups, applies the treatment to only one group (the treatment group), and compares the effects. The two group are equivalent, (e.g. randomly chosen), so the researcher know what results the treatment caused. This design is sound, simple, efficient, and useful.[6]

Pre-test/Post-test Only Control Group

You divide subjects into two randomly chosen groups, test both groups, apply the treatment to only one group (the treatment group), and compare the effects. You know that the group members are equivalent, (e.g. randomly chosen). However, you do not know the *testing effect*, that is, how the pre-test affected the result.

Other Variations

It is possible to add a more independent variables (IV) to see how what effect they make together. This creates more groups, as long as they are all chosen to be equivalent (e.g. randomly chosen). This creates extra hypotheses, which are called *sub-hypotheses*.

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3 Tuckman, 1978, p. 128.
4 Tuckman, 1978, p. 129.
5 Tuckman, 1978, p. 129.
6 Tuckman, 1978, p. 130f.

Four groups, two IV, no pretest:

1. No treatment, post-test (control group)
2. Treatment of first IV, post-test
3. Treatment of second IV, post-test
4. Treatment of both IV, post-test

Four groups, IV, with pretest:

1. Pretest, No treatment, post-test (control group)
2. Pretest, Treatment of first IV, post-test
3. Pretest, Treatment of second IV, post-test
4. Pretest, Treatment of both IV, post-test

Time-Series Design

This method uses only one group as both the control and the treatment group. The researcher gives multiple tests over a longer period to see what change the treatment makes. The natural course of events sets a trajectory, which might change due to the treatment.[7]

1. Test 1
2. Test 2
3. Test 3
4. Test 4
5. Treatment
6. Test 1
7. Test 2
8. Test 3
9. Test 4

Co-relational Study

The researcher compares two groups to find out whether they correlate on a certain variable. However, the data do not allow any conclusions about causation.[8]

1. Test group 1
2. Test group 2

Sample vs. Norms

This design involves comparing a sample (a group of participants) to an established set of norms or a reference group. The norms could be data collected from the general population or a similar group. The goal is to see if the sample's characteristics, behaviors, or scores differ significantly from the norms. This design is often used in psychological assessments or educational testing.

For example, you might want to test if a group of children in a specific school has higher reading scores compared to the average reading scores of children in other schools.

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[7] Cf. Tuckman, 1978, p. 133-36.

[8] Tuckman, 1978, p. 148.

Quasi Experimental Designs

A quasi-experimental design has most of the features of an experimental design, but is done in real-world situations, not in the artificial contexts of experiments. Instead of using random selection for groups, they use pre-existing groups and use other methods to ensure their equivalence. Most experimental designs can be adapted for quasi experiments.

Ex Post Facto Designs

These designs are examinations of things that have already been done, and are not created and controlled by the researcher. Instead of creating new groups, the researcher selects subjects in a way that will ensure that groups are equivalent.[9]

Spoiler Effects

Research can be spoiled by the unanticipated effects of researchers and subjects' attitudes or preconceived ideas.[10]

The Hawthorne Effect

Problem. If people know that they are part of an experiment, they behave differently from how they would act if they didn't know. They often try to make the experiment a "success".

Solutions. Quasi experimental approaches might be better.

The US research ethics requirements has generous exemption categories. The US research ethics requirements also allows subjects to authorize researchers to not disclose or to deceive them about the purpose of the research. (CFR §46.104 (d) (3) (iii))

Ethical Disclosure Bias

Problem: Researchers are normally required to disclose the purpose of research to subjects to get their informed consent, but this can defeat the purpose of the research.

Solutions:

Post facto approaches might be better.

Include a group with no treatment at all.

The US research ethics requirements has generous exemption categories. The US research ethics requirements also allows subjects to authorize researchers to not disclose or to deceive them about the purpose of the research.[11]

The Pygmalion Effect (also known as the Rosenthal effect)

The Pygmalion Effect is also known as the Rosenthal effect.

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9 Tuckman, 1978, p. 147f

10 Adapted from "Deadly mistakes" Ross Woods. Rev. 2018, 2022.

11 Code of Federal Regulations (US government), §46.104. See also §46.104 (d) (3) (iii).

Problem. People perform *better* when *more* is expected of them. It is a kind of self-fulfilling prophecy; if teachers expect children to do better, then they probably will.

Solutions.

1. Post facto approaches might be better.
2. Include a group with no treatment at all.
3. The US research ethics requirements has generous exemption categories.
4. The US research ethics requirements also allows subjects to authorize researchers to not disclose or to deceive them about the purpose of the research.[12]

The Golem Effect

Problem. This is the opposite of the Pygmalion effect. It refers to the phenomenon in which people perform *worse* when *less* is expected of them. It is the same kind of self-fulfilling prophecy; if teachers expect children to do worse, then they probably will.

Solutions:

1. Post facto approaches might be better.
2. Include a group with no treatment at all.
3. The US research ethics regulations have generous exemption categories.[13]
4. The US regulations also allow subjects to authorize researchers to not disclose or to deceive them about the purpose of the research.[14]

The Placebo Effect

Problem. Sick people often get better if they believe in the medicine, even if the medicine is an inert placebo, for example a pill that contains only sugar or flour.

Solution.

Use three groups:

1. Control group 1: placebo treatment
2. Control group 2: no treatment
3. Treatment group

To measure the placebo effect, compare the results of the placebo group with the group without treatment. To measure the effect of the treatment, compare the treatment group with the other two groups.

For example, a researcher ran an experiment with three groups. The placebo and the treatment groups had the same improvement, but the group without treatment showed no improvement. In other words, improvement was the result of the placebo effect.

Confirmation Bias

Problem: Researchers unconsciously tend to notice data that is consistent with their beliefs, and tend to ignore data that is not.

Solution: Create hypotheses and use research designs that are not biased toward particular conclusions.

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[12] Code of Federal Regulations §46.104 (d) (3) (iii).

[13] Code of Federal Regulations §46.104

[14] Code of Federal Regulations §46.104 (d) (3) (iii).

Testing Bias

Problem: When subjects are given a pre-test and a post-test, the first test trains them in how to react in the second test.

Solution: A use a design with only post-test.

Conflict of Interest

Problem: When commercial companies fund researchers to evaluate their products, researchers tend to give favorable evaluations.

Solution: Research journals now normally require authors to declare any conflict of interest. A blind test is better, when the researcher does not know how the study is funded.

Defining Hypotheses and Variables

Defining hypotheses and variables is part of the task of defining your actual research purpose and your topic. Several types of quantitative research depend on hypotheses.

What is an Hypothesis?

A research hypothesis has the following characteristics:

1. There is only *one* hypothesis per research.
2. The hypothesis compares state a relationship between two variables.
3. The hypothesis represents both conceptual and concrete aspects.
4. It uses specific language:

a. It is written in the present tense.
b. It uses unbiased language.
c. It is *one* statement that centers on *one* finite verb. (it is not a cluster of statements.)

5. It is not known whether or not it is true.
6. It is plausible; it is worth investigating because it might be true.
7. It can be tested to find out whether or not it is true.

PICOT hypotheses

In some fields, the hypothesis should follow the PICOT format. It is useful for summarizing research questions, but can also be useful for hypotheses:

P – Population refers to the sample of subjects you wish to recruit for your study. There may be a fine balance between defining a sample that is most likely to respond to your intervention (e.g. no co-morbidity) and one that can be generalized to patients that are likely to be seen in actual practice.

I – Intervention refers to the treatment that will be provided to subjects enrolled in your study.

C – Comparison identifies what you plan on using as a reference group to compare with your treatment intervention. Many study designs refer to this as the control group. If an existing treatment is considered the 'gold standard', then this should be the comparison group.

O – Outcome represents what result you plan on measuring to examine the effectiveness of your intervention. Familiar and validated outcome measurement tools relevant to common chiropractic patient populations may include the Neck Disability Index or Roland-Morris Questionnaire. There are, typically, a multitude of outcome tools available for different clinical populations, each having strengths and weaknesses.

T – Time describes the duration for your data collection.[15]

Examples of PICOT research questions[16]

- In adult patients with total hip replacements (Population), how effective is pain medication (Intervention) compared to aerobic stretching (Comparison) in controlling post operative pain (Outcome) during the perioperative and recovery time (Time)?
- Does telelmonitoring blood pressure (I) in urban African Americans with hypertension (P) improve blood pressure control (O) within the six months of initiation of the medication (T)?
- For patients 65 years and older (P), how does the use of an influenza vaccine (I) compared to not received the vaccine (C) influence the risk of developing pneumonia (O) during flu season (T)?

Examples of PICOT hypotheses

- In adult patients with total hip replacements (Population), pain medication (Intervention) is more effective compared to aerobic stretching (Comparison) in controlling post operative pain (Outcome) during the perioperative and recovery time (Time).
- Telelmonitoring blood pressure (I) in urban African Americans with hypertension (P) improves blood pressure control (O) within the six months of initiation of the medication (T).
- For patients 65 years and older (P), the use of an influenza vaccine (I) influences the risk of developing pneumonia (O) compared to not received the vaccine (C) during flu season (T).

Sub-hypotheses

Some research is so complex that it is best to include sub-hypotheses. A sub-hypothesis is a component of an hypothesis:

1. It is a statement that centers on one finite verb.
2. It is not known whether or not it is true.
3. It is plausible.
4. It can be tested to find out whether or not it is true.
5. A group of sub-hypotheses can be tested to demonstrate together whether or not the main hypothesis is true.

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[15] Guyatt G, Drummond R, Meade M, Cook D. *The Evidence Based-Medicine Working Group Users' Guides to the Medical Literature.* 2nd edition. McGraw Hill; Chicago: 2008. Cited in "What is your research question? An introduction to the PICOT format for clinicians" John J. Riva, BA, DC, Keshena M.P. Malik, BSc, DC, Stephen J. Burnie, BSc, DC, MSc,‡ Andrea R. Endicott, LLB, MPPAL,£ and Jason W. Busse, DC, PhD *The Journal of the Canadian Chiropractic Association* 2012 Sep; 56(3): 167–171. (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3430448/#b5-jcca_v56_3_167_commentary)

[16] Anon. "Evidence Based Practice." https://libraryguides.nau.edu/c.php?g=665927&p=4682772 Viewed March 19, 2025.

Main Hypothesis
The academic performance of university students does not differ significantly between those who study mainly online and those who study in face-to-face courses on campus.

Sub-Hypotheses
1. The Grade Point Average (CPA) of students who mainly take online courses is not significantly different from the GPAs of those who mainly take face-to-face courses on campus.
2. Engagement levels of students who primarily take online courses are not significantly different from the engagement levels of those who mainly take face-to-face courses on campus.
3. The amount of time spent on online course materials has no significant relationship to students' performance in examinations.
4. There is no significant difference in academic performance based on students' prior experience with online learning.

Variables

A variable is a factor that fluctuates according to context. When defining your topic for quantitative research, you will also need to define variables. In quantitative research, independent and dependent must be measurable as categories or numbers:
1. An *independent variable* (IV) is a variable that researchers can manipulate to measure the effect on the dependent variable.
2. A *dependent* variable (DV) is a variable that researchers can measure to know the effect of the independent variable. The dependent variable is the outcome that the researcher measures or analyzes.
3. A *control* variable is a factor held constant to avoid interfering with the effect of the independent variable.
4. *Confounding* variables are uncontrolled variables that change the effect of the independent variable.

Variables come in different kinds, which affects the choice of statistical analysis. (More about that later on.) These are the main kinds:
1. *Nominal*: Categories without a natural order (e.g., gender, race).
2. *Ordinal*: Ranked categories (e.g., satisfaction levels).
3. *Interval*: Numerical scales without a true zero (e.g., temperature in Celsius).
4. *Ratio*: Numerical scales with a true zero, enabling meaningful ratios (e.g., weight, height).

Two Other Terms for Hypotheses

These are called hypotheses but they actually refer to the relationship between variables:
1. A *null hypothesis,* called (H0), means that there is no relationship between the independent and dependent variables.

2. An *alternative hypothesis* (HA or H1) suggests a significant effect or relationship exists.

5

The Research Cycle

The general outline of a quantitative research project is the same as that of qualitative research. This means that other sources will explain how do tasks common to all research, e.g. find a topic, review literature, edit the document.

The major difference for quantatitive research is that it requires a body of qualitative research or a review of mature literature to decide on a testable topic and a research questions. It is also used to write and justify data collection, for example, to write questions in a questionaire.

The outline for quantitative research is as follows:

1. Define the research problem.
2. State the research question or hypothesis and revise it until it is accurate. This involves deciding the variables.
3. Review the literature.
4. Define the population[17].
5. Choose a research design.
6. Unless you already have a dataset, you need to decide:

a. A sampling method.
b. Data collection methods.

7. Write proposals and get all necessary approvals, for example:
    a. Your institution's approval
    b. Ethical approval
    c. Approval to work inside any organization where you will collect data.
8. If you don't already have a dataset, you need to write tools to collect new data, for example, surveys, experiments, or observations.
9. Gather data.
10. Clean the data by deleting mistakes and inconsistencies.
11. Validate the data. Check the reliability and validity of your measurement tools:
    a. Reliability: E.g use Cronbach's alpha for internal consistency of survey scales.
    b. Validity: Confirm content validity by ensuring the tools accurately capture the variables.
12. Analyze data. This normally involves using a computer to apply an existing statistical procedure, and it gives a statistical result.
13. Present results in tables, graphs, and written interpretations, ensuring transparency and reproducibility.
14. Interpret the statistical result to draw conclusions that answer the original research question.

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[17] *Population*: the group of people you want to study.

15. The research then resumes the same cycle as qualitative research. This involves writing discussion and conclusion chapters, and editing the whole document into its final form (e.g. a report or dissertation).

6

Overview of Types

All quantitative research uses statistical methods to process numerical data and support findings, and the steps in each kind of quantitative research are similar or essentially the same.

The list below gives an overall map of the different kinds of common quantitative methods:

1. *Description*. A type of quantitative research that requires a carefully developed research design to ensure valid and reliable results.
2. *Surveys*. Cross-sectional surveys. Observational surveys that collect data from a sample of a target population at a specific point in time.
3. *Correlation*. Correlation quantifies the relationship between two variables. This is a non-experimental kind of research that identifies relationships between two or more variables without the researcher controlling or manipulating them.
4. *Hypothesis testing*. A key part of quantitative research and data analysis that helps determine if there is a relationship between independent and dependent variables.
5. *Experimentation*. Experiments involve manipulating an independent variable and measuring how it affects dependent variables.
6. *Quasi-Experimental.* This approach is similar to experimental design but lacks random assignment, making it more feasible for real-world settings.
7. *Causal-comparative research*. This kind of quantitative research examines cause-effect relationships in retrospect between a dependent and an independent variable.
8. *Predictive research.* This approach uses existing data to predict future outcomes or behavior.
9. *Longitudinal*. This approach is used when the goal is to study changes over time. It involves repeated observations or measurements of the same variables over a long period.

The next series of chapters goes through these approaches in more detail.

7

Description

Example 1

In the county of Meadowbrook, researcher Dr. Emily Carter conducted a study to examine the average screen time among teenagers in urban, suburban, and rural settings. She enlisted three high schools: Central High in the bustling city center, Oakwood High in the peaceful suburbs, and Lakeside High in the rural outskirts.

With consent, students aged 13 to 17 installed screen-tracking applications on their smartphones to monitor daily usage over a two-month period

Dr. Carter collected data over a month. The analysis revealed that urban teens averaged 8 hours of screen time daily, suburban teens 7 hours, and rural teens 6 hours. These findings align with broader trends indicating higher screen usage in urban areas (Smith 2023, Jones, 2024) . This research offers valuable insights for parents and educators aiming to promote balanced screen habits among teenagers across different environments and tailored to each community's unique context.

Example 2

In the bustling city of Techville, startup founder Jane Mitchell launched ShopEase, a new online shopping platform. To assess customer satisfaction, she employed a quantitative descriptive research approach.

Jane designed a structured survey featuring closed-ended questions, such as rating overall satisfaction on a scale from 1 to 10 and indicating the likelihood of recommending ShopEase to others. She distributed the survey via email to 1,000 recent users, achieving a 60% response rate.

Analyzing the numerical data, Jane calculated an average satisfaction score of 8.2 and found that 75% of respondents were likely to recommend the platform. These insights enabled her to identify areas for improvement and informed strategic decisions to enhance the user experience.

Example 3

In the city of Edutown, institutional researcher Maria Lopez conducted a quantitative descriptive study to analyze demographic trends in enrollment at the local university, Edutown State College, over the past five years. She collected enrollment data from 2020 to 2024, focusing on variables such as age, gender, and ethnicity.

Her analysis revealed a 10% decline in overall enrollment, mirroring national trends of decreasing college attendance (Crabtree 2023; Appleton, 2024). Notably, female enrollment increased by 14%, while male enrollment saw a modest 3% rise (Cf. Green 2023). Additionally, Hispanic student enrollments increased significantly, aligning with broader demographic shifts in higher education (Fiddle and Gruen, 2024). Maria's findings provided Edutown State College administrators with critical insights to inform strategic planning and resource allocation, ensuring the institution adapts effectively to evolving student demographics.

About Descriptive Research

Use descriptive research when you want to a detailed snapshot of your subjects. It describes and documents the characteristics, behaviors, or conditions of a specific population or phenomenon. It does not explore cause-and-effect relationships but provides detailed information about “what is” rather than “why.”

You don’t have to do descriptive research in isolation; descriptive data is most useful if used in other methods.

However, if used alone, it has fairly limited application is real research. It is sometimes used as a training exercise for undergraduates. It is also used to collect feedback. However, it is no different from ordinary in-house feedback on commercial product.

Steps to Use Descriptive Research

1. Define the research objective.
2. Specify the question you want to answer or the phenomenon you want to describe, for example, “What is the average time college students spend on social media daily?”
3. Select the population, that is, identify the group (or groups) you want to study.
4. Decide on a sampling method, for example:

a. Simple random sampling ensures everyone in the population has an equal chance of being included.
b. Stratified sampling divides the population into subgroups (e.g., age, gender) and samples proportionally.
c. Convenience sampling is practical for exploratory studies but limits generalizability.

5. Decide how you will recruit respondents.
6. Decide on what specific data you will collect.
7. Write data-gathering tools that will provide accurate, consistent data:

a. Surveys or questionnaires for attitudes or behaviors.
b. Observational checklists for behavior tracking.
c. Existing records for objective data like sales or attendance figures.

8. Test the tools to ensure they are clear and effective:

a. Start with a colleague to get feedback, and make any improvements
b. Then test the tool on a small group of the population, and make any improvements.

9. Collect data

a. Administer surveys, conduct observations, or gather records. In doing so, ensure that participants understand how to respond accurately.

10. Validate the data for reliability and validity:

a. Reliability tests: Test-retest reliability ensures consistency over time.
b. Content validity: Confirm the tool measures what it is intended to measure.

11. Analyze the data using descriptive statistical procedures, for example:
12. Measures of central tendency: mean, median, mode, skewness.

a. Measures of dispersion (data spread): standard deviation, range.
b. Frequency distributions: Use tables, graphs, or charts to summarize categorical data. Graphs are most visual. You can put short tables in the text, but put long tables belong in an appendix; the data might be essential, but they break up the text and make it difficult to read.

13. Interpret the results. Summarize key findings without inferring cause-and-effect relationships. For example: “The average time spent on social media by college students is 3.5 hours daily, with a standard deviation of 1.2 hours.”
14. Report findings. Discuss patterns, trends, or anomalies, and present the results using graphs, charts, and tables for clarity. Put tables of raw data in an appendix.

Common Problems and How to Avoid Them

1. Sampling bias
   a. Problem: Non-representative samples skew results.
   b. Solution: Use random or stratified sampling to ensure diversity.
2. Measurement errors
   a. Problem: Data collection tools might give inaccurate results.
   b. Solution: Validate and pilot-test tools before full data collection.
3. Over-generalization
   a. Problem: Conclusions are drawn beyond the studied population.
   b. Solution: Clearly define the scope and limitations of the study.
4. Lack of context
   a. Problem: Results lack depth without qualitative input.
   b. Solution: Complement descriptive findings with qualitative research if context is essential.

Task

You will need one or two journal articles that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer’s methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

8

Surveys

Example 1

In the city of Worktown, HR manager Lisa Chen conducted a quantitative survey to assess the impact of remote work on employee productivity at TechSolutions Inc. She distributed an online questionnaire to 200 employees, incorporating standardized productivity metrics and Likert-scale questions. The survey achieved an 85% response rate.

Analysis revealed that 60% of respondents reported increased productivity while working remotely, citing factors like reduced commute times and flexible schedules. However, 25% experienced challenges, including feelings of isolation and difficulties in communication.

These findings align with broader research indicating that remote work can enhance productivity for many employees, though it may also introduce certain challenges (pmc.ncbi.nlm.nih.gov).

Lisa's study provided TechSolutions' leadership with data-driven insights to refine their remote work policies, aiming to sustain productivity gains while addressing employee well-being.

Example 2

In the coastal city of Greenport, sociologist Dr. Emma Johnson conducted a quantitative survey to gauge public perceptions of climate change policies.

She randomly selected 500 residents to participate in a structured questionnaire, which included Likert-scale questions assessing support for various environmental initiatives, such as renewable energy investments and carbon taxation. The survey achieved a 70% response rate.

Analysis revealed that 65% of respondents viewed climate change as an immediate threat, aligning with global sentiments reported by the International Monetary Fund (IMF, 2022) Additionally, 60% supported implementing stricter environmental regulations, while 25% expressed concerns about potential economic impacts.

These findings provided local policymakers with valuable insights into community attitudes, aiding in the development of balanced and effective climate policies.

Example 3

In the city of Autoville, market analyst John Davis conducted a quantitative survey to identify factors influencing the adoption of electric vehicles (EVs) among residents. He distributed structured questionnaires to 1,000 randomly selected individuals, achieving a 75% response rate. The survey included Likert-scale questions assessing the importance of various factors, such as environmental concerns, government incentives, charging infrastructure, and vehicle cost.

Analysis revealed that 70% of respondents considered environmental benefits a significant motivator for adopting Evs. However, 65% cited the high upfront cost as a major barrier, reflecting broader trends where EV affordability remains a concern for middle-income consumers. Additionally, 60% of participants indicated that the availability of charging stations would greatly influence their decision, underscoring the need for robust infrastructure to support EV adoption.

John's findings provided local policymakers and automotive industry stakeholders with valuable insights to develop strategies promoting EV adoption tailored to community preferences and concerns.

About Surveys

Use surveys to collect standardized data from a large group of people to explore trends, attitudes, opinions, or behaviors. It is useful when you want to generalize findings to a broader population based on a representative sample. However, it is most useful when used as a data collection method for another kind of study.

Steps to Use the Survey Method

1. Define the research question; start with a clear question you want to answer. For example, “What factors influence college students' career preferences?”
2. Identify the population; decide who you wil survey (for example, college students in the U.S.).
3. Decide an a sampling method, for example:
   a. Simple random sampling ensures every individual in the population has an equal chance of selection.
   b. Stratified sampling divides the population into subgroups (e.g., age, gender) and samples from each subgroup.
   c. Systematic sampling selects participants at regular intervals from a list.
4. Design the survey (See later chapter)
5. Test and refine the survey (See later chapter)
6. Distribute the survey
7. Collect Data.
8. Validate the Data
   a. Use tests like Cronbach's alpha* to check the reliability of scales.
   b. Assess content validity by ensuring the survey covers all aspects of the research topic.
9. Analyze the data with statistical procedures:
   a. Descriptive Statistics: Summarize data (e.g., means, medians, frequencies).
   b. Inferential Statistics: Test hypotheses (e.g., t-tests*, chi-square tests*, regression analysis*).
10. Interpret and report results. Translate your numerical results into meaningful insights and connect them to the research question.

Common Problems and How to Avoid Them

1. Low response rate

a. Solution: Offer incentives, send reminders, and keep the survey short.
2. Biased sampling
a. Solution: Use random or stratified sampling to ensure representation.
3. Poorly designed questions
a. Solution: Avoid leading, double-barreled, or confusing questions. Pilot-test the survey.

A Question

You might have noticed that description and surveys look to be almost the same. So what's the difference?

In quantitative research methods, "description" and "surveys" are related but distinct concepts. Here's how they differ:

Description

The *purpose* of descriptive research is to describe characteristics of a phenomenon or a population. It involves gathering detailed information to represent the current state of affairs. Its *methods* often involve observational techniques, case studies, or statistical descriptions (like averages, percentages, and distributions) without necessarily manipulating variables. The *focus* of descriptive reserch is on "what" is happening rather than the reasons behind it. It paints a picture of a situation by describing the features or attributes of a group or variable.

As an example, the researcher might describe the age, gender, and educational background of a population in a city.

Surveys

The *purpose* is to collect data such as information about opinions, behaviors, or characteristics of a population. They typically involve structured questionnaires or interviews. As for *method*, surveys involve asking a sample of respondents a set of questions to collect data. The data can be used for descriptive, correlational, or even experimental analysis, depending on the design. The *focus* also differs. Surveys focus on gathering data from a sample, which can then be generalized to a larger population. They are often used to explore the "how" and "why" behind the observed phenomena. For example**,** a researcher might conduct a survey to understand consumer preferences or attitudes toward a new product.

Key Differences

Nature of data: Descriptive research is more about summarizing or categorizing data, while surveys are a tool to gather specific data from individuals through questions.

Purpose: Descriptive research primarily seeks to describe existing conditions or phenomena, while surveys are more focused on collecting data to analyze behaviors, opinions, or attitudes, which can be used for various types of analysis.

In summary, descriptive research is about understanding and describing a situation, and surveys are a method of gathering data to inform various types of research, including descriptive research.

Task

You will need one or two journal articles that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer's methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

9

Correlation

Example 1

In the suburban town of Brookdale, high school counselor Sarah Mitchell conducted a correlational study to examine the relationship between physical activity levels and academic performance among male and female students. She collected data from 200 students, recording their weekly hours of physical activity and corresponding grade point averages (GPAs).

The analysis revealed a positive correlation between physical activity and academic performance for both genders. Specifically, students engaging in at least 5 hours of physical activity per week had an average GPA of 3.5, compared to 3.0 for those with less than 2 hours of activity. These findings align with previous research indicating that physical activity can enhance cognitive function and academic achievement (Brewski 2019; Klottam, 2022).

Sarah's study suggests that promoting regular physical activity may be beneficial for students' academic success. However, causation has not been demonstrated. It could be that academically successful students are more likely to be physically active. Further research would be necessary to indicate causation.

Example 2

In the city of Harrisville, psychologist Dr. Emily Harris conducted a correlational study to examine the relationship between social media usage and self-esteem among high school and college students. She distributed a structured questionnaire to 300 students—150 high schoolers and 150 college students—assessing their daily social media usage in hours and their self-esteem levels using a standardized scale.

The analysis revealed a significant negative correlation between social media usage and self-esteem in both groups. Specifically, for every additional hour spent on social media daily, self-esteem scores decreased by 0.5 points. These findings align with previous research indicating that increased social media usage negatively correlated with self-esteem among adolescents and young adults (pmc.ncbi.nlm.nih.gov).

Causation was not proven. Perhaps social media usage supports healthy self-esteem in young individuals. However, it is also possible that individuals with low self-esteem want to increase their social media usage. Further study is necessary to establish causation.

Example 3

In the city of Mountainview, economist Dr. Laura Green conducted a correlational study to examine the relationship between income levels and job satisfaction among urban and rural employees. She surveyed 500 participants—250 from urban areas and 250 from rural areas—collecting data on their annual income and job satisfaction using standardized scales.

The analysis revealed a positive correlation between income and job satisfaction in both groups. Specifically, for every $10,000 increase in annual income, job satisfaction scores increased by 0.5 points on a 10-point scale. However, the strength of this correlation was stronger among urban employees compared to their rural counterparts. These findings align with previous research indicating that income levels correlate with job satisfaction, with variations across different settings (pmc.ncbi.nlm.nih.gov). These results do not demonstrate causation; perhaps employees with good job satisfaction could be given roles with higher incomes. On the other hand, it is also possible that that targeted income-related strategies could affect job satisfaction. Either way, future research should test causation, for example, that targeted income-related strategies affect job satisfaction.

About Correlation

This method can uncover meaningful patterns and differences in relationships across multiple groups, providing valuable insights for decision-making or further research.

Use correlational research when you want to explore the relationship between two variables without manipulating them. It is commonly used when experimentation is impractical, unethical, or unnecessary. For example, it can examine whether and how two variables (e.g., study hours and grades) are related across two groups (e.g., students in different classes).

You can also compare more than two groups when you want to examine relationships between variables across multiple categories or subgroups. This method allows you to explore whether the strength or direction of a relationship differs among different groups. (In this sense, the “direction of a relationship” refers to causation.) For example, you might study how the correlation between exercise and stress levels varies among age groups (teens, adults, and seniors).

Steps For Using Correlational Research

By following these steps, researchers can explore meaningful relationships between variables, compare them across groups, and derive insights without manipulating the studied factors.

1. Define the research question
2. Specify the variables you want to study and the groups you are comparing.
3. Example for two groups: "Is there a relationship between study time and test scores among science and arts students?"
4. Examples for more than two groups:
5. “Is there a relationship between between exercise and stress levels among age groups (teens, adults, and seniors).”
6. “Does the correlation between social media usage and academic performance differ among high school, college, and graduate students?”
7. Identify the population.
8. Choose a sampling method.

a. Sampling methods for two or more) groups must ensure that all groups are adequately represented for meaningful comparisons:

i. Simple random sampling: Ensures every individual in the population has an equal chance of being selected.
ii. Stratified sampling: In order to ensure that both groups are adequately represented in the sample, divide the population into subgroups (e.g., age groups) and sample from each subgroup proportionally.
iii. Cluster sampling: Use predefined groups (e.g., schools, workplaces) for convenience and representation.

9. Select variables to measure

a. For comparing two groups, identify the **two continuous variables** to be measured e.g., hours of study (independent variable) and test scores (dependent variable); , hours of social media use (independent variable) and GPA (dependent variable).
b. For comparing more than two groups, choose variables that are continuous or ordinal.
c. Ensure the variables are quantifiable and relevant to the research question.

10. Develop data-gathering tools to measure variables consistently across groups (See chapter 18.) Standardize tools to ensure comparability across groups. Examples of tools include:
    a. Surveys or questionnaires for self-reported behaviors.
    b. Official records or tests for objective measures like grades or performance.
11. Collect data
    a. Administer the tools to participants in both/all groups.
    b. Ensure all participants understand how to provide accurate data.
    c. Ensure that the data collection process is uniform across groups to avoid introducing bias.
12. Clean data
13. Validate the data; check the reliability and validity of the tools:

a. Reliability tests: Cronbach's alpha* (for consistency of responses and internal consistency of survey scales).
b. Content validity: Ensure the tools measure what they are intended to. Check that the accurately capture the variables.

14. Analyze the data
    a. To interpret data from two groups, groups, use regression analysis*, ANOVA,* or hypothesis testing, to interpret the data. You can also use:
        i. Pearson's Correlation Coefficient (r)*: Measures the strength and direction of the linear relationship between the two variables.
        ii. Spearman's Rank-Order Correlation (ρ)*: Used if data is ordinal or non-linear.

b. For more than two groups, you have other options:
    i. Use Pearson's correlation coefficient to assess the strength and *direction of relationships* within each group.
    ii. Comparative Analysis: Use Fisher's Z-test* to compare correlation coefficients between groups.
    iii. Multigroup Path Analysis* or Moderation Analysis*: Explore how group membership influences the relationship between variables.
c. Compare correlations across the groups to observe any differences.

Direction of the linear relationship

The “direction of the linear relationship” in the context of Pearson’s Correlation Coefficient simply tells how the variables move in relation to each other, that is whether the two variables tend to increase or decrease together.

- *Positive direction (positive correlation, r > 0)*: As one variable increases, the other also tends to increase. For example, as study time increases, exam scores might also increase.
- *Negative direction (negative correlation, r < 0)*: As one variable increases, the other tends to decrease. For example, as the number of hours spent watching TV increases, exam scores might decrease.
- *No direction (r = 0)*: There is no linear relationship between the two variables.

15. Interpret Results
    a. Correlation results range from -1 to +1:
        i. **+1:** Strong positive relationship (both variables increase together).
        ii. **-1:** Strong negative relationship (one variable increases, the other decreases).
        iii. **0:** No relationship.
    b. Example 1: "There is a moderate positive correlation (r = 0.6) between study hours and test scores for science students, but no correlation (r = 0.1) for arts students."
    c. Example 2 “Social media usage is strongly negatively correlated with GPA for high school students (r = -0.7), moderately negatively correlated for college students (r = -0.4), and uncorrelated for graduate students (r = 0.1).”
    d. Example 3: "Social media usage is strongly negatively correlated with GPA for high school students (r = -0.7), moderately negatively correlated for college students (r = -0.4), and uncorrelated for graduate students (r = 0.1)."
    e. Examine whether the correlation differs significantly among groups.
16. Present findings as group-specific correlations and statistical comparisons.
17. Present results in tables, graphs, and written interpretations, ensuring transparency and reproducibility.
18. Report conclusions
    a. Present group-specific correlations, statistical comparisons, differences between groups, implications and limitations of the study.

Common Problems and How to Avoid Them

1. Unequal group sizes
    a. Problem: Small groups may not provide reliable results.
    b. Solution: Use stratified sampling to ensure groups are balanced.
2. Confounding variables
    a. Problem: An unknown third variable (an uncontrolled factor) might have influenced the relationship between the variables.
    b. Solution: Use statistical controls or collect data on potential confounders. Measure and control for confounding variables using statistical techniques like ANCOVA*.

3. Misinterpretation of results
   a. Problem: Correlation is often mistaken for causation.
   b. Solution: Clearly state that correlation does not imply causation.
4. Misinterpreting results
   a. Problem: Correlation differences between groups may be attributed to chance.
   b. Solution: Use statistical tests (e.g., Fisher's Z-test) to confirm significance.
5. Measurement errors
   a. Problem: Data inaccuracies can weaken the correlation.
   b. Solution: Use validated and reliable tools for data collection.
6. Measurement inconsistencies across groups
   a. Problem: Tools may perform differently in different groups.
   b. Solution: Use standardized tools validated for all subgroups.

Task

You will need one or two journal articles or a dissertation that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer's methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

10

Hypothesis Testing

Example 1

In the city of Rocky Cove, nutritionist Dr. Alice Thompson tested the hypothesis, "The Smith Diet Plan reduces cholesterol levels more effectively than a standard diet." She recruited 100 participants, randomly assigning 50 to follow the new diet and 50 to maintain their usual eating habits.

Over a three-month period, Dr. Thompson measured participants' cholesterol levels at the start and end of the study. Using a two-sample t-test, she compared the mean cholesterol reductions between the two groups. The results indicated a statistically significant greater reduction in cholesterol levels among those on the new diet, supporting the hypothesis that the new diet plan is more effective than the standard diet. This study s an example of how hypothesis testing can be applied in a practical setting to assess the efficacy of dietary interventions.

Example 2

In the city of Tall Pines, high school teacher Mr. James Carter conducted a study to test the hypothesis on whether exam scores were significantly different between students taught using online and in-person methods. He randomly assigned 100 students to two groups: 50 received instruction through online classes, while the other 50 attended traditional in-person classes. After a semester, Mr. Carter administered the same standardized exam to all students.

Using a two-sample t-test, he compared the mean exam scores of both groups. The results indicated a statistically significant difference, with the in-person group outperforming the online group by an average of 5 percentage points.

This finding suggests that in-person instruction may lead to higher academic performance compared to online learning. Further research would be required to examine the factors that caused the difference.

Example 3

In the county of Lone Ridge, a western suburb of the city of Bayswater, energy consultant Sarah Mitchell conducted a study to test the hypothesis on whether households using renewable energy sources experienced a greater reduction in energy costs compared to those using non-renewable sources. She selected 100 households, randomly assigning 50 to install solar panels and 50 to continue using traditional energy sources.

Over a year, Sarah collected data on each household's monthly energy expenses. Using a two-sample t-test, she compared the average annual energy costs between the two groups. The results indicated a statistically significant difference, with the renewable energy group reporting an average 20% reduction in energy costs, supporting the hypothesis that renewable energy adoption leads to lower household energy expenses.

About Hypothesis Testing

Use hypothesis testing when you aim to make inferences about a population based on sample data. It is appropriate when you want to test whether a claim, assumption, or prediction about a population parameter is likely true or false. For example, testing whether a new teaching method improves student performance compared to a traditional method.

Steps to Use Hypothesis Testing

1. Define the research question and hypotheses
a. Null Hypothesis (H_0): States there is no effect or no difference (e.g., "The new teaching method has no effect on student performance").
b. Alternative Hypothesis (H_1 or H_a): States there is an effect or difference (e.g., "The new teaching method improves student performance").
2. Choose the population and sampling method. Possible methods include:
a. Simple Random Sampling: Ensures every individual has an equal chance of being selected.
b. Stratified Sampling: Ensures representation of subgroups within the population.
c. Systematic Sampling: Selects every nth individual from a list.
3. Collect the required dta.
a. Data should align with the hypothesis being tested, such as:
    i. Test scores to evaluate performance.
    ii. Survey responses to measure satisfaction.
    iii. Time measurements for speed or efficiency.
b. Tools must be valid and reliable. They must consistently and accurately measure the variables, and can be:
    i. Standardized tests for performance.
    ii. Calibrated equipment for physical measurements.
    iii. Pre-validated questionnaires for opinions or behaviors.
4. Set the significance level (α)
a. Choose the probability threshold for rejecting the null hypothesis, typically 0.05 (5%). This represents a 5% chance of wrongly rejecting H_0 when it is true.
5. Conduct the hypothesis test
a. Choose the statistical test based on data type and research design:
    i. t-test*: Compare means of two groups.
    ii. ANOVA*: Compare means of three or more groups.
    iii. Chi-Square Test*: Analyze relationships between categorical variables.
    iv. Regression Analysis*: Test relationships between variables.
    v. Z-test*: Compare sample and population means when the population standard deviation is known.
6. Analyze the results
a. Calculate the p-value: The probability of observing your data if H_0 is true.
    i. If $p \leq \alpha$: Reject H_0 and accept H_1 (evidence supports a significant effect).
    ii. If $p > \alpha$: Fail to reject H_0 (no significant evidence to support H_1).

7. Validate the data
a. Check data quality and consistency before analysis:
b. Reliability Tests: Ensure repeated measurements produce similar results (e.g., Cronbach's alpha*).
c. Normality Tests: Use tests like Shapiro-Wilk* or Kolmogorov-Smirnov* to confirm data distribution.
8. Report Findings
a. Clearly present the hypothesis, methodology, results, and interpretation.
b. Use graphs and tables to summarize key statistics.

Results Produced by Hypothesis Testing

1. Statistical significance: Indicates whether the observed effect or difference is likely due to chance.
2. Effect size: Measures the magnitude of the difference or relationship.
3. Confidence intervals: Provides a range of values where the true population parameter is likely to fall.

Common Problems and How to Avoid Them

1. Small sample size
   a. Problem: Reduces the reliability of results.
   b. Solution: Use power analysis to determine the required sample size.
2. Misinterpreting p-values
   a. Problem: Assuming a small p-value proves causation.
   b. Solution: Emphasize context and effect size alongside p-values.
3. Violation of assumptions
   a. Problem: Tests assume conditions like normality and homogeneity of variance*.
   b. Solution: Check assumptions using tests like Levene's test* or data transformations*.
4. Biased sampling
   a. Problem: Skewed samples reduce generalizability.
   b. Solution: Use random sampling techniques and ensure diversity.

Task

You will need one or two journal articles or a dissertation that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer's methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

12

Cause and Effect Experiments

Example 1

In the city of Red Plains, Dr. Emily Harris, a clinical researcher, conducted a controlled experiment to evaluate the effectiveness of a new antihypertensive drug in reducing blood pressure. She recruited 200 participants diagnosed with hypertension, randomly assigning 100 to receive the new medication and 100 to a placebo group. Over a 12-week period, Dr. Harris monitored participants' blood pressure levels at regular intervals.

Upon analysis, she found that the group receiving the new drug experienced a significant average reduction of 15 mmHg in systolic blood pressure, compared to a 5 mmHg reduction in the placebo group. This statistically significant difference supports the hypothesis that the new drug is more effective than the placebo in lowering blood pressure.

This study is an example of the use of controlled experiments to establish cause-and-effect relationships in medical research.

Example 2

In the town of Ocean Bay, sleep researcher Dr. Emily Harris conducted a controlled experiment to investigate the impact of screen time on sleep quality among teenagers. She recruited 100 adolescents, randomly assigning 50 to limit their screen usage to one hour per day for a month, while the other 50 maintained their usual screen habits. Throughout the study, Dr. Harris monitored participants' sleep patterns using wearable devices that tracked sleep duration and quality.

The analysis revealed a significant improvement in sleep quality among the reduced screen time group, with an average increase of 30 minutes in sleep duration and 20% fewer sleep disturbances. These findings suggest that reducing screen time can positively affect sleep quality in teenagers.

Example 3

In the city of Hugo River, high school teacher Mr. James Carter conducted a controlled experiment to assess the impact of different teaching methods on students' test scores. He randomly assigned 100 students to three groups: one received traditional lecture-based instruction, another engaged in interactive, student-centered learning, and the third participated in a blended approach combining both methods. After a semester, Mr. Carter administered the same standardized test to all groups.

The results revealed that the student-centered group achieved the highest average score, followed by the blended group, with the lecture-based group scoring the lowest. This statistically significant difference indicates that teaching methods can influence academic performance, with interactive and blended approaches yielding better outcomes.

About Cause and Effect Experiments

Use an experiment when your purpose is to establish cause-and-effect relationships between variables. This is ideal when you can manipulate one or more independent variables (what you change) to observe their effect on dependent variables (what you measure).

Steps to Use the Experimental Method

1. Define the research question
a. Start with a clear question or hypothesis. For example, “Does a higher temperature improve plant growth?”
2. Identify variables
a. Independent Variable: The factor you manipulate (e.g., temperature).
b. Dependent Variable: The outcome you measure (e.g., plant height).
c. Control Variables: Factors kept constant to avoid confounding effects (e.g., type of plant, soil type, length of time measured).
3. Choose a sampling method, for example:
a. Random sampling ensures every member of the population has an equal chance of being selected.
b. Random assignment places participants into experimental and control groups, reducing bias.
4. Design the experiment
a. Create at least two groups:
    i. An experimental group: Exposed to the independent variable (e.g., higher temperature).
    ii. A control Group: Not exposed to the independent variable (e.g., normal temperature).
b. Decide the method of data collection (e.g., observation, measurements).
5. Set up data-gathering tools
a. Use tools that are accurate and consistent (e.g., thermometers, rulers, timers).
b. Ensure tools are calibrated to avoid measurement errors.
6. Conduct the experiment
a. Apply the independent variable to the experimental group.
b. Keep conditions identical between groups except for the independent variable.
7. Collect data
a. Measure and record the dependent variable consistently across all participants.
b. Ensure all observations are precise and objective.
8. Check the validity of the data
a. Use internal validity tests to confirm the results are due to the independent variable, not other factors.
b. Conduct reliability checks to ensure the experiment is repeatable with similar results.
9. Analyze the data
a. The statistical procedures may be:
    i. T-tests*: Compare the means of two groups.
    ii. ANOVA*: Compare means across multiple groups.
    iii. Regression Analysis*: Explore relationships between variables.

b. Look for significant differences between the experimental and control groups.
10. Interpret and report results
a. Discuss whether the data supports your hypothesis.
b. Highlight any implications or limitations of the study.

Common Problems and How to Avoid Them
1. Confounding variables
a. Solution: Identify and control all possible variables that could influence the outcome.
2. Small sample size
a. Solution: Use a large enough sample to ensure the results are generalizable.
3. Measurement errors
a. Solution: Use standardized and calibrated tools. Train researchers to ensure consistency.

Is Hypothesis Testing Different from Cause and Effect Experiments?

Yes, hypothesis testing and cause-and-effect experiments are related but distinct concepts within quantitative research methodology.

Hypothesis Testing

Hypothesis testing is a statistical procedure used to determine whether there is enough evidence to support or reject a proposed hypothesis. It involves comparing observed data against a null hypothesis (H_0) (which usually states that there is no effect or no difference) and an alternative hypothesis (H_1) (which suggests the presence of an effect or difference).Statistical tests (e.g., t-tests, ANOVA, chi-square tests) are used to analyze data and determine significance levels (p-values).

Cause-and-Effect Experiments

These experiments aim to establish causality, meaning that one variable directly influences another. They use an experimental design, such as a randomized controlled trial (RCT), where researchers manipulate the independent variable (IV) and measure its effect on the dependent variable (DV). Common methods include pre-test/post-test designs, control and experimental groups, and randomization to reduce biases.

Key Differences

Feature	Hypothesis Testing	Cause-and-Effect Experiments
Purpose	Tests whether a hypothesis is supported by data	Determines if one variable directly causes a change in another
Focus	Evaluates relationships, differences, or patterns in data	Establishes causality through controlled manipulation
Methods	Uses statistical tests (t-test, chi-square, regression)	Uses experimental designs (RCTs, lab experiments)
Example	Testing if students with more study hours score higher	Conducting an experiment where one group receives tutoring and another does not

In conclusion, all cause-and-effect experiments involve hypothesis testing, but not all hypothesis testing involves cause-and-effect experiments. If you only analyze associations or correlations, you are testing a hypothesis but not necessarily proving causation. Cause-and-effect relationships require careful experimental control to rule out confounding variables.

Task

You will need one or two journal articles or a dissertation that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer's methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

13

Quasi-experimental

Example 1

Dr. Martinez, a high school math teacher, wanted to test whether a flipped classroom model would improve student performance compared to traditional teaching. She conducted a quasi-experimental study at Lincoln High School, using two sections of her Algebra II class. The first section followed a traditional lecture-based approach, while the second section received pre-recorded video lessons to watch at home, with in-class time dedicated to problem-solving and discussions. Over a semester, she measured student performance through quizzes, exams, and engagement surveys. Using statistical analysis, she compared the mean test scores of both groups. Results showed that students in the flipped classroom scored, on average, 12% higher and reported greater confidence in problem-solving. Dr. Martinez concluded that the flipped model could enhance learning outcomes, though factors like student motivation and home environment also played a role.

Example 2

Dr. Patel, a hospital administrator, wanted to evaluate the impact of a new telemedicine program on patient satisfaction and health outcomes. She conducted a quasi-experimental study at Riverdale Community Hospital, comparing two groups of patients with chronic conditions. One group continued with traditional in-person visits, while the other used telemedicine for follow-ups and consultations. Over six months, Dr. Patel collected data on patient satisfaction surveys, appointment adherence rates, and health indicators like blood pressure and glucose levels. Using statistical analysis, she found that telemedicine patients reported 20% higher satisfaction and showed improved health management. However, some struggled with technology access. The study suggested telemedicine could enhance care but required support for digital accessibility.

Example 3

Economic researcher Lisa Chen wanted to assess whether increasing the minimum wage would reduce poverty rates in Brookside County. She conducted a quasi-experimental study by comparing Brookside, which recently raised its minimum wage, to a neighboring county with similar demographics that kept its wage unchanged. Over a year, Lisa collected data on employment rates, household incomes, and the percentage of residents living below the poverty line. Using statistical analysis, she found that poverty rates in Brookside declined by 8%, while the control county saw little change. However, small businesses in Brookside reported higher labor costs, leading to slight reductions in hiring. Lisa concluded that raising the minimum wage could help reduce poverty, but its broader economic effects required further study.

About Quasi-experimental Methods

Quasi-experimental methods enable researchers to evaluate interventions in real-world conditions while addressing the limitations of not having randomized control groups. They are appropriate when you aim to study cause-and-effect relationships but cannot randomly assign participants to groups due to ethical, practical, or logistical constraints. Instead, researchers use pre-existing groups or implement interventions in real-world settings.

Steps to Use Quasi-Experimental Methods

Example: "Does a new reading program improve literacy rates in schools?"

1. Define the research objective
a. Clearly state the research question and identify:
    i. Independent Variable (IV): The intervention or treatment.
    ii. Dependent Variable (DV): The measurable outcome affected by the IV.
2. Design the study. Common quasi-experimental designs include:
a. Non-Equivalent Groups Design: Compares two or more groups that were not randomly assigned.
b. Pretest-Posttest Design: Measures the outcome before and after the intervention in one group.
c. Interrupted Time Series Design: Examines outcomes over time before and after the intervention.
3. Choose the population and sampling method
a. Sampling methods are:
    i. Purposive sampling: Selects participants based on specific characteristics (e.g., schools with a reading program).
    ii. Convenience Sampling: Uses participants who are easily accessible.
b. Match groups on key characteristics (e.g., age, socioeconomic status) to reduce bias.
4. Identify data to collect
a. Data should align with the IV and DV:
    i. Quantifiable outcomes (e.g., test scores, attendance rates).
    ii. Background information to control for confounders (e.g., demographics).
5. Develop data-gathering tools.
a. Tools must be reliable and valid for the context. Examples include:
    i. Surveys or questionnaires.
    ii. Standardized tests.
    iii. Observation checklists.
    iv. Historical data (e.g., school records).
6. Implement the Intervention
a. Apply the intervention to the experimental group while the comparison group does not receive it.
b. Ensure consistency in how the intervention is delivered.
c. Control for confounding variables. Identify potential confounders (e.g., teacher qualifications, prior knowledge) and see statistical controls or matching techniques to minimize their impact.*

7. Collect data
a. Measure the DV at appropriate time points (e.g., before and after the intervention).
b. Ensure standardized data collection procedures across groups.
8. Validate the data
a. Use reliability and validity tests to ensure accurate measurements:
    i. Reliability Tests: Check for consistency (e.g., test-retest reliability).
    ii. Construct Validity: Ensure the tool measures the intended variable.
9. Use statistical procedures to analyze the data, for example:
    i. t-tests*: Compare pretest and posttest results.
    ii. ANOVA*: Compare means across multiple groups or time points.
    iii. Regression Analysis*: Control for confounders and examine relationships between variables.
    iv. Effect Size (e.g., Cohen's d *): Assess the strength of the intervention's impact.
b. Interpret results
    i. Summarize findings, discuss implications, and acknowledge limitations. For example: "The reading program increased test scores by 15%, with a significant difference between the experimental and comparison groups ($p < 0.05$)."

Results Produced by Quasi-Experimental Methods
1. Causal Inferences: Indicates potential cause-and-effect relationships between IV and DV.
2. Effect Sizes: Measures the strength of the intervention's impact.
3. Practical Applications: Provides actionable insights in real-world settings.

Common Problems and How to Avoid Them
1. Selection bias
a. Problem: Pre-existing differences between groups may confound results.
b. Solution: Match groups on key characteristics or use statistical adjustments.
2. Confounding variables
a. Problem: Extraneous factors may influence outcomes.
b. Solution: Identify potential confounders and control for them in analysis.
3. Lack of randomization
a. Problem: Reduces internal validity.
b. Solution: Use robust statistical techniques to strengthen causal claims.
4. Measurement issues
a. Problem: Tools may not accurately measure the DV.
b. Solution: Validate tools and ensure consistency in data collection.

Task

You will need one or two journal articles or a dissertation that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer's methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.

3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

14

Causal comparative

Example 1

Dr. Amanda Lewis, an education researcher, wanted to examine whether gender influences math performance among high school students. She conducted a causal-comparative study at Westwood High, analyzing standardized test scores from 200 male and 200 female students in Algebra II. She ensured both groups had similar socioeconomic backgrounds and prior math achievement levels. Using statistical analysis, she compared the average test scores of male and female students. Results showed no significant difference in overall performance, though male students scored slightly higher in problem-solving, while female students excelled in mathematical reasoning and written explanations. Dr. Lewis concluded that gender alone did not determine math performance, but learning styles and classroom engagement might play a role, warranting further investigation.

Example 2

Education researcher Dr. Sophia Ramirez wanted to examine how socioeconomic status (SES) affects access to higher education opportunities. She conducted a causal-comparative study using data from 300 high school seniors in three SES groups: low, middle, and high income. She analyzed college application rates, scholarship awards, and acceptance into four-year universities. Using statistical analysis, she found that students from higher-income families applied to and were accepted into prestigious universities at higher rates, while low-income students relied more on financial aid and attended community colleges. Middle-income students had mixed results, depending on available family support. Dr. Ramirez concluded that socioeconomic status significantly influences access to higher education, highlighting the need for more targeted financial aid and mentorship programs for disadvantaged students.

Example 3

Human Resources researcher Daniel Rivera wanted to examine whether remote workers experienced different levels of job satisfaction compared to on-site employees. He conducted a causal-comparative study at Horizon Tech, analyzing survey responses from 150 remote and 150 on-site employees. The survey measured factors like work-life balance, productivity, and overall job satisfaction on a standardized scale. Using statistical analysis, Daniel found that remote workers reported higher satisfaction with flexibility and work-life balance, while on-site employees valued in-person collaboration and company culture. However, both groups had similar

overall job satisfaction scores. Daniel concluded that work location alone did not determine satisfaction, but personal preferences and job roles played a role. His findings helped Horizon Tech refine its hybrid work policies to improve employee well-being.

About Causal-comparative

By using causal-comparative approach, researchers can examine cause-and-effect relationships in situations where experimental manipulation is not possible. It is useful when you cannot manipulate the Independent variable (IV) directly due to ethical, practical, or logistical constraints. Instead, researchers compare two or more pre-existing groups based on the IV to examine differences in the DV.

Steps to Use Causal-Comparative Research

1. Define the research objective
a. Clearly identify the IV (categorical, pre-existing groups) and DV (quantifiable outcome).
b. Example: “Does type of school (public vs. private) affect students’ academic performance?”
2. Choose the population and sampling method
a. Suitable sampling methods may include:
    i. Purposive Sampling: Select participants based on their membership in pre-existing groups (e.g., public or private school students).
    ii. Matched Sampling: Pair participants from different groups based on shared characteristics to control for confounding variables.
    iii. Random Sampling: Helps generalize findings to a larger population when feasible.
3. Identify data to collect
a. Independent Variable (IV): Pre-existing groups (e.g., type of school, gender, or socioeconomic status).
b. Dependent Variable (DV): Measurable outcomes affected by the IV (e.g., test scores, job satisfaction).
4. Develop data-gathering tools
a. Ensure tools are valid and reliable for measuring the DV across groups. Examples include:
    i. Standardized tests for academic performance.
    ii. Surveys or questionnaires for attitudes or behaviors.
    iii. Official records (e.g., attendance, grades).
5. Control for confounding variables
a. Identify variables that could influence the DV (e.g., parental involvement, teacher qualifications). Use strategies such as:
    i. Statistical controls (e.g., ANCOVA)*.
    ii. Matching participants with similar characteristics across groups.
6. Collect data
a. Gather data from participants in all groups.
b. Ensure that data collection procedures are consistent to minimize bias.
7. Validate the data
a. Use reliability and validity tests:
    i. Internal Consistency (Cronbach’s Alpha*): Ensures survey items measure the same construct.
    ii. Construct Validity: Confirms the tool measures the intended variable.
8. Analyze the data
a. Suitable statistical procedures may include:

i. t-tests*: Compare the means of two groups (e.g., public vs. private school students).
ii. ANOVA*: Compare the means of three or more groups.
iii. Effect Size (e.g., Cohen's d*): Assess the strength of differences.
iv. Regression Analysis*: Control for confounding variables to isolate the IV's effect on the DV.

9. Interpret results
a. Describe the differences between groups and the possible causal link between the IV and DV. For example: "Students from private schools scored an average of 10 points higher on standardized tests than those from public schools ($p < 0.05$)."

10. Report findings
a. Present results with statistical evidence, visual aids (graphs, tables), and a discussion of limitations.

Common Problems and How to Avoid Them

1. Selection bias
a. Problem: Pre-existing groups may differ in ways unrelated to the IV.
b. Solution: Match participants or use statistical controls to adjust for confounders.
2. Lack of randomization
a. Problem: Causal relationships may be harder to establish without random group assignment.
b. Solution: Clearly state the limitations and use alternative techniques to strengthen causal inference (e.g., propensity score matching).
3. Confounding variables
a. Problem: Extraneous factors may influence the DV.
b. Solution: Identify and statistically control for confounders during analysis.
4. Misinterpretation of causation
a. Problem: Correlations may be mistaken for causal relationships.
b. Solution: Use careful language to describe findings (e.g., "associated with" rather than "caused by").

Task

You will need one or two journal articles or a dissertation that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer's methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

15

Predictive

Example 1

Marketing analyst Jake Thompson wanted to predict customer churn for BrightWave Telecom. He analyzed data from 5,000 customers, examining purchase history, service interactions, and satisfaction survey scores. Using statistical modeling, he identified key patterns: customers were more likely to cancel their subscriptions if they had made fewer purchases in the last six months, made multiple service complaints, and had low satisfaction scores. His predictive analysis showed that customers with all three risk factors had a 75% chance of churning within the next three months.

Based on his findings, BrightWave implemented targeted retention strategies, offering discounts and improved customer support to at-risk customers. After six months, churn rates decreased by 15%. Jake's study demonstrated how predictive research can help businesses proactively improve customer retention and loyalty.

Example 2

Dr. Emily Carter, a data analyst at Ridgeway Medical Center, wanted to predict patient outcomes based on demographic information, medical history, and treatment data. She analyzed records from 10,000 patients with chronic conditions, using statistical modeling to identify risk factors for hospital readmission. Her analysis revealed that older patients with a history of multiple hospital visits and inconsistent medication adherence had a 60% higher chance of readmission within three months.

Using these insights, Ridgeway Medical implemented a targeted follow-up program, offering personalized care plans and medication reminders. After six months, readmission rates dropped by 20%. Dr. Carter's research demonstrates how predictive analytics can help healthcare providers improve patient care and reduce hospital strain by identifying high-risk individuals early.

Example 3

Dr. Mark Reynolds, an education researcher at Crestwood High School, wanted to predict student performance on final exams based on academic records and study habits. He analyzed data from 500 students, examining past grades, attendance, and self-reported study routines. Using statistical modeling, he found that students with consistent study schedules, high homework completion rates, and strong mid-term scores had an 85% likelihood of earning an A or B on final exams. Conversely, those with irregular study habits and frequent absences were at higher risk of failing.

Based on these insights, the school introduced early intervention programs, including study workshops and tutoring. After implementation, at-risk students improved their scores by an average of 12%. Dr. Reynolds' research showed how predictive analytics can support academic success through proactive intervention.

About predictive research

Predictive research is powerful when used appropriately, allowing researchers and organizations to forecast future outcomes and make informed decisions based on historical data. Use predictive research when you want to use existing data to predict future outcomes or behavior. It is often used in fields such as marketing, healthcare, economics, and education to forecast trends, behaviors, or events based on past patterns. For example, it can predict customer purchase behavior or forecast student academic performance based on prior data.

Steps to Use Predictive Research

1. Define the research question
a. Identify the dependent variable (DV) that you want to predict, and determine the independent variables (IVs) that may influence the prediction. For example: "Predicting customer churn (DV) based on customer satisfaction, purchase history, and service interactions (IVs)."
2. Select the data and sampling method
a. Sampling methods may include:
    i. Random Sampling: Best for generalizing to a larger population.
    ii. Stratified Sampling: Ensures representation of key subgroups within the population, useful if predicting for distinct groups.
    iii. Convenience Sampling: Often used in exploratory predictive research but may reduce generalizability.
b. Collect data that is relevant to the prediction and has historical context. The data should ideally be from reliable and representative sources.
3. Collect the required data
a. Data should be based on measurable outcomes. For predictive research, the data you collect is typically historical or transactional data.
b. Data can be numerical (e.g., sales figures, test scores) or categorical (e.g., customer satisfaction levels, education level).
c. Ensure that the data is clean, reliable, and relevant to the prediction task.
4. Develop data-gathering tools
a. Tools may be:
    i. Surveys/Questionnaires: If collecting data directly from people.
    ii. Databases: Historical records or transactional data (e.g., CRM systems for customer data).
    iii. Observational tools: If measuring certain variables over time (e.g., sensor data for predicting equipment failure).
b. Ensure tools are valid and reliable
c. Gather a large enough dataset to make meaningful predictions.
5. Choose the predictive model
a. Choose a predictive model based on the nature of your data and research goal:
    i. Linear Regression: Predicts continuous outcomes (e.g., predicting sales revenue).
    ii. Logistic Regression: Predicts binary outcomes (e.g., predicting whether a customer will buy a product: Yes/No).

iii. Decision Trees/Random Forests: Predicts outcomes using hierarchical decision rules (useful for both continuous and categorical outcomes).
iv. Time series nalysis: Forecasts future values based on historical data (e.g., predicting stock prices).
v. Machine Learning Models (e.g., Neural Networks): Advanced techniques that can predict complex patterns in large datasets.

6. Pre-process and clean the data
a. Data cleaning: Remove outliers, handle missing data (e.g., through imputation), and standardize data if necessary.
b. Feature engineering: Create new variables from existing data that may improve model performance (e.g., creating "customer age groups" from raw age data).
c. Normalize or scale data if required by the model (e.g., for regression or neural networks).

7. Build and train the model
a. Split the data into training and testing sets (e.g., 70% for training, 30% for testing).
b. Use the training data to build the predictive model and the test data to validate its accuracy.

8. Validate and evaluate the model
a. Cross-validation: Use techniques like k-fold cross-validation* to ensure the model generalizes well.
b. Use validation metrics:
   i. R^2 or Adjusted R^2 * (for regression models): Measures how well the model fits the data.
   ii. Confusion Matrix* (for classification models): Measures the accuracy, precision, recall, and F1 score.
   iii. Mean Squared Error (MSE)*: Measures the average of the squared differences between the predicted and actual values.
   iv. The area Under the ROC Curve (AUC)*: For binary classifiers, assesses the trade-off between true positives and false positives.

9. Make predictions
a. Once the model is validated, use it to make predictions on new, unseen data. Example: Predicting customer churn next month based on current and past customer data.

10. Interpret and report the results
a. Communicate the results clearly:
   i. What predictions were made?
   ii. How accurate are the predictions?
   iii. What are the practical implications of the predictions?
b. Use visualizations such as charts, graphs, and tables to help stakeholders understand the predictions and their significance.

Data imputation
Compensating for missing data by either deleting the record or replacing it with something that will have minimum effect. For example it can be estimates if data are missing at random. It can also be done statistically.[18]

Results Produced by Predictive Research

1. Predictions: The main output of predictive research is the forecasted values or outcomes based on the model.
2. Model performance metrics include accuracy measures (e.g., R^2, AUC) that evaluate how well the model predicts new data.
3. Insights for decision-making: Predictive models often provide actionable insights for decision-making (e.g., what factors are most likely to influence customer churn).

Common Problems and How to Avoid Them

1. Overfitting
   a. Problem: The model performs well on training data but poorly on test data because it "memorizes" the training set instead of generalizing.
   b. Solution: Use cross-validation, regularization techniques, and ensure the model is not too complex relative to the dataset size.
2. Data quality issues
   a. Problem: Poor data quality (missing data, outliers) can lead to inaccurate predictions.
   b. Solution: Clean the data thoroughly, use imputation techniques for missing data, and handle outliers appropriately.
3. Model selection
   a. Problem: Using an inappropriate model for the type of data (e.g., using linear regression for non-linear relationships).
   b. Solution: Choose the right model based on data type and research goal. Test multiple models and compare performance.
4. Bias in data
   a. Problem: Data may be biased or unrepresentative of the population, leading to inaccurate predictions.
   b. Solution: Ensure that the sample is representative, and use techniques like stratified sampling to avoid bias.

Task

You will need one or two journal articles or a dissertation that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)

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[18] See Jakobsen JC, Gluud C, Wetterslev J, Winkel P. "When and how should multiple imputation be used for handling missing data in randomised clinical trials - a practical guide with flowcharts." *BMC Med Res Methodol*. 2017 Dec 6;17(1):162. doi: 10.1186/s12874-017-0442-1. PMID: 29207961; PMCID: PMC5717805.

1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer's methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

16

Longitudinal

Example 1

Dr. Rachel Simmons, a cardiologist at Westbrook Medical Institute, conducted a 20-year longitudinal study to examine how long-term physical activity influences cardiovascular health in adults. She tracked 1,500 participants, collecting data on exercise habits, blood pressure, cholesterol levels, and heart disease incidence every five years. Statistical analysis revealed that adults who engaged in at least 150 minutes of moderate exercise per week had a 40% lower risk of developing heart disease compared to sedentary individuals. Additionally, active participants maintained healthier blood pressure and cholesterol levels over time. However, those who reduced activity levels later in life saw increased cardiovascular risks. Dr. Simmons' research reinforced the long-term benefits of consistent physical activity and helped shape public health recommendations on heart disease prevention.

Example 2

Dr. Linda Hayes, an education researcher at Riverstone School District, conducted a 10-year longitudinal study to examine how students' reading abilities develop over time and the impact of early interventions. She tracked 500 students from kindergarten through high school, collecting data on reading assessments, intervention participation, and academic performance. Using statistical analysis, Dr. Hayes found that students who received early literacy interventions showed significant improvement in reading skills, with most maintaining strong literacy throughout their school years. In contrast, students who did not receive interventions had slower reading development and lower academic performance in later grades. The study highlighted that early intervention programs not only boosted short-term reading skills but also had lasting effects on overall academic success. Dr. Hayes' findings emphasized the importance of early support in literacy development.

Example 3

Dr. Sarah Lopez, a psychologist at Hillcrest Research Institute, conducted a 30-year longitudinal study to explore how childhood trauma affects mental health outcomes in adulthood. She tracked 1,000 participants, gathering data on early experiences of trauma (such as abuse or neglect) and assessing mental health indicators, such as anxiety, depression, and PTSD, throughout their lives. By analyzing the data, Dr. Lopez found that individuals who experienced trauma in childhood had a significantly higher likelihood of developing mental health issues in adulthood, particularly anxiety and depression. However, those who received early therapeutic interventions showed fewer long-term mental health problems. Her research highlighted the enduring impact of childhood trauma and emphasized the importance of early mental health support in mitigating long-term psychological effects.

About Longitudinal Research

Longitudinal research is invaluable when the focus is on studying change, development, or the effects of time on certain variables, helping researchers track trends and make forecasts based on past patterns.

Use a longitudinal approach when you want to study changes over time. This method involves repeated observations or measurements of the same variables over a long period. It is particularly useful when researchers want to understand how things evolve or predict future trends based on patterns of change. This method is commonly used in fields like psychology, medicine, education, and social sciences.

When to use it:

1. To examine how a group or individual evolves over time.
2. To track the impact of a particular treatment or intervention over an extended period.
3. To study developmental trends or cause-and-effect relationships.

Longitudinal research is not well suited to student dissertations where students collect their own evidence because the time span is too long.

Steps to Use Longitudinal Research

1. Define the research objective
2. Clearly define the research question. For example, "How do smoking habits influence lung health over a 10-year period?"
3. Identify the variables that will be tracked over time:
a. Independent Variables (IVs): Factors that might influence the dependent variable (e.g., smoking habits, diet, exercise).
b. Dependent Variables (DVs): Outcomes that are affected by the IVs (e.g., lung function, health status).
4. Select the study design
a. Types of Longitudinal Designs:
    i. Cohort study: Follows a group of people who share a common characteristic or experience over time.
    ii. Panel study: Collects data from the same subjects at multiple time points.
    iii. Retrospective longitudinal study: Looks at past records and data to follow changes over time (e.g., analyzing historical health data).
b. Choose the design based on your research goals and available resources.
5. Choose the population
6. Choose a sampling method and ensure the sample size is large enough to detect changes over time and to provide statistical power.
a. Random Sampling: Ideally used if you want to generalize findings to a larger population.
b. Stratified Sampling: Useful when specific subgroups (e.g., age groups, socio-economic status) need to be represented equally.
c. Convenience Sampling: May be used if access to specific populations or participants is limited, but it might reduce generalizability.
7. Determine the data to be collected, for example:

i. Demographic data: Age, gender, education, and other characteristics that may influence the outcome.
ii. Behavioral data: Changes in behavior (e.g., smoking, exercise, medication adherence).
iii. Health data: Physical measures (e.g., weight, blood pressure) or psychological assessments.

b. Ensure that the variables selected are relevant to the research question and can be consistently measured over time.

8. Develop Data-Gathering Tools

a. For example:
i. Surveys/Questionnaires: To collect information on behaviors, attitudes, and self-reported health.
ii. Interviews/Focus Groups: In-depth data collection, especially for subjective variables like quality of life or mental health.
iii. Medical or Health Records: For objective data on health status or clinical measures.
iv. Observation Tools: If direct observation is necessary (e.g., behavioral change).

b. Ensure that data collection tools remain consistent over time to reduce measurement errors.

9. Collect data over time

a. Collect data at multiple time points (e.g., yearly, biannually). Each time point will provide a snapshot of the dependent variable(s) at that time.
b. Plan the timing: Ensure consistent intervals between data collection to capture changes accurately.
c. Ensure follow-up with participants to maintain a consistent sample size across waves of data collection.

10. Check data validity

a. Internal Validity: Ensure the results reflect the true relationship between IVs and DVs, not due to other external factors.
b. External Validity: Ensure the results can be generalized to other groups, especially if sampling was non-random.
c. Use validity checks (e.g., test-retest reliability, consistency between different measures).

11. Analyze the data using statistical procedures, e.g.:

a. Descriptive Statistics: Used to summarize the data over time (mean, standard deviation).
b. Growth Curve Modeling*: Analyzes individual changes over time.
c. Repeated Measures ANOVA*: Used when analyzing data collected at more than two time points, comparing means across time.
d. Linear Regression*: Can predict future outcomes based on changes over time (e.g., predicting future health outcomes based on current data).
e. Survival Analysis*: Used when the research goal is to track when an event will occur (e.g., predicting when a health event might happen).

12. Interpret and report the results

a. Interpret how the data has changed over time and what trends can be observed.
b. Identify any longitudinal trends, that is, any patterns or significant changes over the periods of observation.

c. Present findings in graphs or charts that illustrate change over time.
d. Discuss potential causality or correlations (though longitudinal studies often cannot fully prove causality).

Results Produced by Longitudinal Research
1. Trends Over Time: Insight into how specific variables evolve or change over a given period.
2. Cause-and-Effect Relationships: By observing data over time, researchers can infer causality or correlation between variables.
3. Impact of Interventions: Understand how changes in policy, behavior, or treatment impact individuals or groups.

Common Problems and How to Avoid Them
1. Participant drop-out (Attrition)
a. Problem: Participants dropping out over time can skew results and reduce sample size.
b. Solution: Ensure strong participant retention strategies (e.g., regular follow-ups, incentives for continued participation) and track the reasons for attrition.
2. Data inconsistency
a. Problem: Variations in data collection tools or protocols over time may result in inconsistent measurements.
b. Solution: Standardize data collection methods and ensure training for all researchers involved.
3. Measurement bias
a. Problem: Changes in how variables are measured may lead to inaccurate conclusions.
b. Solution: Use the same measurement tools and protocols throughout the study period.
4. Sample size issues
a. Problem: Small sample sizes may not give sufficient power to detect significant changes or effects.
b. Solution: Calculate the appropriate sample size beforehand using *power analysis** to ensure you have enough participants.

Task

You will need one or two journal articles or a dissertation that use this kind of quantitative research. (Your instructor might provide them for you or ask you to find your own.)
1. Did the writer follow the research cycle as presented in chapter 5? If not, what was different?
2. Compare the writer’s methodology with the steps presented earlier in this chapter. Were they the same or different? Explain any differences.
3. Evaluate the strengthes and weaknesses of the methodology in the article.
4. What did you personally learn about methodology from the article? Be ready to share what you learned in class.

Power analysis

In this context, “Power analysis” refers to a statistical method used to determine the minimum sample size needed for a study in order to detect an effect, if one actually exists.

In simpler terms, it helps you figure out how many participants you need so that your study has a high chance (or *power*) of correctly identifying a real relationship or difference, while also minimizing the risk of missing it (a Type II error).

Key elements in power analysis include:

- *Significance level (α)*: The threshold for determining statistical significance (often set at 0.05).
- *Effect size*: The expected strength of the relationship or difference you’re trying to detect.
- *Power (1 - β)*: The probability of correctly rejecting the null hypothesis when it is false (commonly set at 0.80 or 80%).
- *Sample size*: The number of participants required to achieve the desired power.

Essentially, power analysis ensures you don't have too few participants (risking inconclusive results) or too many (wasting time and resources).

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Defining populations and samples

When researching human subjects, you need to define who they are clearly and accurately. The particular group of people whom you will research are known as a *population* or sometimes as the *target group* or *target population*. A population is the total group of people of your study

At this stage, you need to define its characteristics so that you know from whom you will select a sample and to whom your conclusions will refer.

What About a Large-scale Problem?

In some cases, you might address a theoretical or a large-scale problem. However, to do any research, you need to select a local population for your study or, if it is a comparative study, multiple local populations. You then draw a sample from this population (or populations).

For example, you want to evaluate the transition to a new national curriculum that affects all school students across the entire nation. However, it would be impractical to define your population as the thousands of school-teachers who implemented the transition across the nation. It would be better to define the population as the teachers in a particular local region to which you have access. In the conclusion of your research you will mention the limitations of your work; in this case that you only studied one region, and other regions might be different.

You should also consider the kind of document. If you are writing a journal article with a limit of 8,000 words, you will probably need to work with a smaller population than if you are writing a dissertation with a limit of 100,000 words.

The Entire Population

In a few cases, you can analyze the entire population. This is most feasible if you have an existing dataset with readily available data for analysis. Examples include government records, academic records, financial information, sales, attendance, website analytics, commercial datasets, and records of performance tests. This is discussed in more detail in the next chapter.

About Sampling

In most cases, however, you cannot get data from everyone in the population, so you need to define a sample. Your choice of method to define a sample is critical for ensuring that data represents the population of interest. It is also critical to determine the sample size based on statistical power and research objectives.

Of the many different kinds of sampling methods, you must choose one that suits your research goals. These are the main candidates:

1. *Random sampling*: Ensures each population member has an equal chance of selection, minimizing bias.
2. *Stratified sampling*: Divides the population into subgroups and samples proportionally, ensuring subgroup representation.
3. *Systematic sampling*: Selects every nth individual from a list. This is simple while also reducing some bias.

Another kind of sample is the *representative sample.* It is the minimum size random sample to ensure statistically that results will represent the whole population. However, it is not feasible for most research projects because it almost always requires an impractically high number of respondents.

Advice and Best Practices

1. Make sure that your sample size is large enough to get meaningful results. Unfortunately, much quantitative research is nearly meaningless because the sample sizes are so small.
2. Use randomization whenever possible to enhance reliability.
3. If possible, avoid convenience sampling for quantitative work. It uses readily available participants but it risks bias and limits generalizability.
4. Snowball samples are not at all suitable; they get data through personal networks when data is inaccessible in the open community. While the data might be good and otherwise inaccessible, the respondents cannot be said to represent the population.

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Data Collection and Data Collection tools

Existing Databases

Existing databases provide readily available data for analysis Examples include government records, academic records, financial information, sales, attendance, website analytics, commercial datasets, and records of performance tests.

They have the following advantages:

1. They save you time and cost.
2. They provide access to large, often representative samples. In some cases, you can use.
3. They allow longitudinal analyses with pre-existing datasets.
4. The data has probably already been anonymized.

However, they also have limitations:

1. Some data may be outdated or irrelevant to specific research questions.
2. The researcher has little or no control over how the data was originally collected.
3. Data collection procedures might have changed over time.
4. The format of the data might present difficulties.
5. Unless you are an insider in the organization, it can be difficult to get permission to use its internal data.

Collecting New Data

When existing data is insufficient, researchers must design and implement their own data collection tools. Examples included online surveys and observation checklists.

Some degree programs require students to demonstrate that they can collect their own data. In other program, students might only be able to use existing datasets. Some allow either.

Ethics

1. Your ethical permission limits you to collecting data according to your research project. It is unethical to collect and store extra data that you do not need.
2. Even if data is anonymous, do not collect enough data to re-identify individuals.
3. Use simple language when communicating to prospective respondents and respondents.
4. Ensure respondents of ethics and what that means, e.g.:

a. your research purpose.
b. Their participation is voluntary.
c. They can drop out at any time without penalty.
d. You will keep their information anonymous, and you will not identify them.

e. You will store data securely and eventually delete it.

Using Interviews

Interviews are only feasible if your sample is quite small; it is not practical to interview large numbers of respondents. It can also be awkward when people feel pushed into the limited answers of closed questions. However, it is most helpful in some circumstances: oral cultures, when the personal connection is essential to get good data, and when working with some kinds of disability.

Steps for Collecting New Data

1. Identify your data needs.
a. Clarify exactly what information you need to meet your research objects and the reasons why. For example:
    i. What information will you need to answer your research question?
    ii. Are you seeking perceptions and attitudes, or factual information?
    iii. Are you seeking propensity to answer in particular ways or pre-existing views.
2. Choose the method that is appropriate for your data needs and research goals, for example:
a. Surveys: Use structured questionnaires to gather responses efficiently.
b. Experiments: Manipulate variables under controlled conditions to observe effects.
c. Physical tests
d. Observation checklists: Collect real-world data through systematic observation.
e. Interviews:
    i. With closed questions
    ii. With open questions where responses can be categorized into statistics
    iii. Write the instrument (see below)
3. Get a colleague to examine the tool. As the writer, you know what you meant, but the colleague will have fresh eyes and might see it differently.
4. Pilot the tool on a small group of the population to identify any issues, then revise it.
a. If the revisions are non-trivial, test it again with a different small group of the population. It is important that they have not seen it before.
5. Decide how you will deliver the tool. In many cases, it will be an online form and you could use an outside service. For example, SurveyMonkey offers customizable templates and advanced analytics, while Google Forms is a free, user-friendly option for simple surveys. By using online forms, you can gather information from very large samples at low cost, and in some cases, all members of the population.
6. Collect data:
a. Administer the tools to participants.
b. Ensure that the data collection process is uniform across groups to avoid introducing bias.
c. Monitor response rates and, if necessary, follow up to reach the desired sample size.

Common Kinds of Questions

1. Most tools start with some demographic Information. Collect basic details (e.g., age group, gender) to contextualize findings.

2. Choose one of the following categories …
3. Likert Scale: most often used to measure opinions, attitudes or perceptions on a five point continuum (e.g., Strongly agree, Agree, Don't know, Disagree, Strongly disagree).
4. Multiple Choice: Choose from a set of predefined answers or categories.

Writing Effective Tools

Writing tools is a specialized skill, even though good tools look very simple and are easy to use. Be prepared to write several drafts a revise them thoroughly.

Here's a checklist:

1. Questions are clear and unambiguous, and each question has one meaning. (Do other people interpret them to mean what you think they mean?)
2. Closed questions cover all possibilities. (You don't want to make people feel forced into giving an answer that does not represent their views or the information they want to present.)
3. They cover the full range of data needed to answer your research question.
4. The language easy to understand for population members.
a. Questions are fairly short, simple, and straightforward.
b. They have no jargon or unfamiliar terminology.
c. Respondents understand each question correctly the *first* time they read it.
5. The question are neutral and avoid bias:
a. The wording does not lead people to favor some answers.
b. The wording does not lead people away from particular others.
c. The wording ensures comparability across groups.
6. Respondents give anonymized responses that protect their identities.
7. Questions do not make respondents feel uncomfortable. For example, they do not make people embarrassed or manipulated, and do not intrude into their privacy (e.g. personal income, etc.).
8. Questions are in an order that makes it easy for respondents to answer.
a. Hint: Start with easy questions about basic demographic information. This makes it easier for them to continue to other questions.
9. Express thanks to respondents for participating. (Some researcher have funding to give a gift card or bookstore discount.)
10. Check for length.
a. Is the questionnaire short enough that people will finish it?
b. Do you know how much time it will take people to finish it?

Another hint: You can repeat questions in very different formats to check whether people answer consistently. If the answers are inconsistent, your software might disregard that data.

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On Data Cleaning

The data you gather might not be perfect; it might have mistakes, inconsistencies, non-standard formats, duplicates, or missing items.

Clean the data by deleting duplicates, removing corrupted data and compensating for missing data by either deleting the record or replacing it with something that will have minimum effect. For example it can be estimates (called imputation) if data are missing at random. It can also be done statistically.[19]

Keep a record of what you do, and do version control so that you know which is your latest version. Clean and accurate data will give better results in statistical tests.

Well-written online forms now reduce the need for data cleaning. Respondents have no way of submitting invalid answers, and they cannot submit their forms unless they have responded to all required questions. When respondents submit a form, the software converts answers to numbers. However a glitch in the software itself will make all collected data unacceptable.

Data cleaning is a different process from data validation, in which a computer checks data against a format and rejects data that does not match it.

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19 See Jakobsen JC, Gluud C, Wetterslev J, Winkel P. "When and how should multiple imputation be used for handling missing data in randomised clinical trials - a practical guide with flowcharts." *BMC Med Res Methodol*. 2017 Dec 6;17(1):162. doi: 10.1186/s12874-017-0442-1. PMID: 29207961; PMCID: PMC5717805.

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About Internal Validity Tests

Internal validity refers to the extent to which an experiment accurately establishes a cause-and-effect relationship between the independent and dependent variables. High internal validity ensures that observed changes in the dependent variable are directly due to the manipulation of the independent variable, not due to extraneous or confounding factors.

Types of Internal Validity Threats and How to Address Them

1. Selection bias
a. This happens when groups are not equivalent at the start of the experiment.
b. Test and solution:
c. Random assignment test: Ensure participants are randomly assigned to experimental and control groups. Verify equivalence by comparing baseline characteristics (e.g., age, gender) across groups using t-tests or chi-square tests.
2. History effect
a. This refers to external events that happened during the experiment and influenced results.
b. Test and solution:
    i. Use control groups to compare outcomes and rule out external influences.
    ii. Keep the study duration short to minimize the impact of external events.
3. Maturation effect
a. Participants naturally change over time and this can affect results. For example, it can be due to aging or fatigue.
b. Test and solution:
    i. Use a pre-test and post-test design to measure changes over time.
    ii. Use a control group to differentiate between maturation effects and the treatment effect.
4. Testing effect
a. Repeated testing influences participants' behavior (e.g., practice effect).
b. Test and solution
    i. Use parallel forms of tests or a Solomon four-group design, which adds groups to isolate the effect of testing.
5. Instrumentation
a. Changes in your measurement tools or methods can affect results.
b. Test and solution:
    i. Calibrate tools and ensure consistency in measurement procedures.

ii. Train observers or raters to minimize variability.

6. Regression to the mean

a. Extreme scores tend to move closer to the average on subsequent testing.

b. Test and Solution:

    i. Include a control group to determine if changes are due to regression or the treatment.

7. Attrition (mortality)

a. When participants drop out of the study, the results become skewed.

b. Test and solution:

    i. Compare characteristics of those who dropped out and those who completed the study.

    ii. Use statistical techniques like *intention-to-treat analysis* to account for missing data.

8. Confounding variables

a. Extraneous variables unintentionally influence the dependent variable.

b. Test and solution:

    i. Identify potential confounders and control them through randomization, matching, or statistical techniques (e.g., ANCOVA).

Intention-to-treat analysis

Intention-to-treat (ITT) analysis is a statistical method used particularly in randomized controlled trials, to include all participants in the groups to which they were originally assigned, regardless of whether they completed the study, adhered to the treatment, or dropped out.

In simpler terms:

- *What it means*: Even if participants don’t follow the study protocol perfectly (e.g., they stop taking the medication or miss sessions), they are still analyzed as part of their original group.
- *Why it's used*: ITT helps maintain the benefits of randomization, reducing bias and providing a more realistic estimate of the treatment’s effectiveness in real-world conditions.
- *How it helps with missing data*: It ensures that missing data from dropouts or non-adherence doesn’t skew the results, offering a more accurate and conservative estimate of the treatment effect.

This method is especially important when accounting for missing data, as it avoids overestimating the effectiveness of an intervention by excluding participants who didn’t complete the study.

Steps for testing Internal Validity

1. Design the experiment carefully

a. Use a randomized controlled trial (RCT) or other rigorous designs to minimize bias.

b. Include control and experimental groups.
2. Pre-test analysis
a. Check for baseline equivalence across groups using statistical tests (e.g., t-tests for means, chi-square for categorical variables).
3. Monitor during the experiment
a. Keep conditions consistent across groups.
b. Document any external events or participant behaviors that could affect outcomes.
4. Post-test analysis
a. Use statistical methods to test for significant differences between groups (e.g., ANOVA, t-tests).
b. Use regression models to control for potential confounders.
5. Use blinding
a. Employ single-blind or double-blind designs to reduce bias from participants or researchers.
6. Conduct sensitivity analyses
a. Explore how robust the findings are to different assumptions (e.g., including or excluding outliers).

Single blind **and** ***double blind***

Single-blind and double-blind experiments are research methods designed to reduce bias in studies, particularly in clinical trials and psychological research.

- In single-blind experiments, the participants do not know which group they are in (e.g., whether they are receiving the actual treatment or a placebo), but the researchers do. This prevents participants' expectations from influencing the results (placebo effect). For example, in a drug trial, participants don't know if they're receiving the real drug or a sugar pill, but the researcher knows who is getting what.
- In double-blind experiments, neither the participants nor the researchers know which participants are receiving the treatment or the placebo. This prevents both participants' and researchers' biases from affecting the results. For example, in the same drug trial, neither the participants nor the researchers know who gets the drug and who gets the placebo until after the data is collected and analyzed. Double-blind studies are considered more reliable because they reduce bias from both sides.

Key Takeaway

Internal validity tests are critical for ensuring that the observed effects in your experiment are truly caused by your independent variable. By addressing threats to internal validity systematically, you can strengthen the credibility of your findings.

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About Data Distributions

Normal vs. Non-Normal Distributions
Normal Distribution: A symmetric bell-shaped curve where most values cluster around the mean. Key characteristics include predictable percentages of data within standard deviations (e.g., 68% within one SD).
Non-Normal Distribution: Skewed or irregular patterns often require non-parametric tests or data transformations to ensure valid analysis.

Measures of Central Tendency
Mean: Represents the average and is sensitive to outliers.
Median: Useful when data is skewed or contains outliers.
Mode: Highlights the most frequent category or value.

Variability
Range: Measures the span of data but is affected by outliers.
Variance: Indicates data spread; larger values signify greater dispersion.
Standard Deviation: Provides a practical measure of variability around the mean, useful for comparing datasets.

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About Analysis Methods

In quantitative research, data analysis normally involves using a computer to apply an existing statistical procedure. Choosing and applying the right tests for your projects looks confusing, so here's a brief guide.

Within-Subject vs. Between-Subject Designs

In a "within-subject design", participants are exposed to all conditions of the independent variable. This has the advantage of reduces variability by using the same participants across conditions, requiring fewer subjects. However it also has a risk of carryover effects (e.g., learning or fatigue) that can influence results. An example of a "within-subject design" is testing the effectiveness of two teaching methods on the same group of students over different periods.

"In a between-subject design", participants are divided into groups, each exposed to different conditions. This eliminates carryover effects and is suitable for irreversible treatments. However, it requires larger sample sizes to account for individual differences. An example of a "between-subject design" is a comparison of test scores of two different groups of students taught by two different methods in separate classrooms.

Validity and Reliability

Researchers need to know whether their data is valid and reliable.

1. *Internal Validity*: Ensures the study accurately measures the intended effect, free from confounding variables.
2. *External Validity*: Indicates how well results generalize to other populations or contexts.
3. *Reliability*:

a. *Internal Consistency*: Consistency of results across items within a test (e.g., Cronbach's Alpha).

b. *Stability*: Consistency of results over time (e.g., test-retest reliability).

Statistical Tests

Quantitative researchers use a variety of statistical methods depending on the research question and data characteristics. Here are key techniques:

1. **p-value**: Measures the probability of observing results as extreme as the sample data if the null hypothesis is true. A smaller p-value (< 0.05) typically indicates statistical significance. Or ??? The **p-value** is a probability that helps determine the significance of your test results in hypothesis testing. It represents the likelihood of observing the data, or something more extreme, if the null hypothesis (H0H_0) is true.
2. **Chi-Square Test**: Examines relationships between categorical variables.

a. *Example*: Testing if gender influences voting preferences.

3. **Cronbach's Alpha**: Assesses internal consistency of a scale or questionnaire. Values closer to 1 indicate high reliability.
    i. *How to Use*: Apply this test during tool validation to ensure consistency among survey items.
4. **Pearson's Correlation (r)**: Evaluates linear relationships between two continuous variables. Values range from -1 to +1.
    i. *Example*: Examining the correlation between study hours and test scores.
5. **Spearman's Rho (ρ)**: Measures monotonic relationships for ordinal or non-linear data.
    i. *Example*: Analyzing the relationship between job satisfaction and rank.
6. **Mann-Kendall test:** Analyzing the difference between later-measured data and earlier-measured data.

Type I Errors and Type II Errors in Statistics

A Type I Error is a false positive. It occurs when a null hypothesis (H0H_0) is rejected even though it is true. A type I error means that you detected an effect or difference that does not actually exist. It is denoted by α\alpha, which is the significance level (e.g., 0.05 or 5%). Type I Errors lead to unnecessary actions or treatments, increased costs, or incorrect decisions based on false positives.

A type II error is a false negative. It occurs when a null hypothesis (H0H_0) is not rejected even though it is false. It means that you failed to detect an effect or difference that really does exist. It is d:enoted by β\beta, with 1−β1 - \beta representing the test's power. Type II Errors result in missed opportunities, underestimation of risks, or continuation of ineffective practices.

Balancing the risk of Type I and Type II errors is critical in hypothesis testing and often involves choosing an appropriate significance level (α\alpha) and ensuring adequate sample size to increase test power (1−β1 - \beta).

Here is the same information in a table:

Aspect	Type I Error	Type II Error
Null Hypothesis (H0H_0)	Incorrectly rejected	Incorrectly accepted
Outcome	False positive	False negative
Implication	Claiming an effect exists when it does not.	Missing an effect that actually exists.

Examples of Type I Errors

1. **Medical Research**
a. **Scenario**: Testing a new drug.
b. **Error**: Concluding the drug is effective when it actually has no effect.
2. **Legal System**
a. **Scenario**: Determining guilt in a criminal trial.
b. **Error**: Convicting an innocent person (rejecting the "not guilty" null hypothesis).
3. **Quality Control**

a. **Scenario**: Testing the quality of a manufactured product.
b. **Error**: Rejecting a batch of products as defective when they actually meet quality standards.

Examples of Type II Errors

1. **Medical Research**
a. **Scenario**: Testing a new treatment for a disease.
b. **Error**: Concluding the treatment is ineffective when it actually works.
2. **Legal System**
a. **Scenario**: Determining guilt in a criminal trial.
b. **Error**: Failing to convict a guilty person (accepting the "not guilty" null hypothesis).
3. **Marketing**
a. **Scenario**: Testing the effectiveness of a new advertisement.
b. **Error**: Concluding that the ad does not increase sales when it actually does

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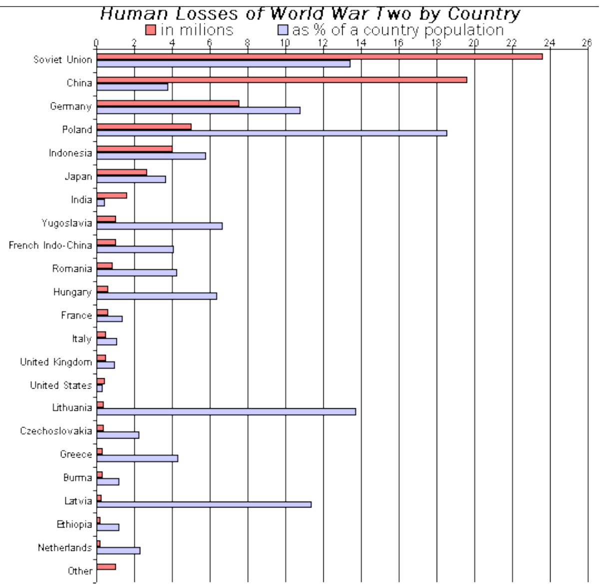
Using Graphs

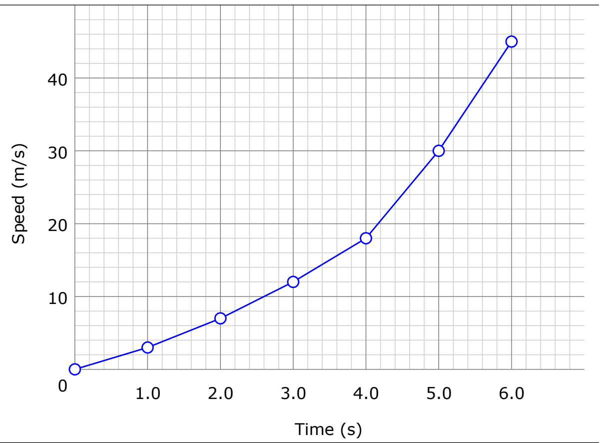
Graphs are very effective for presenting quantitative data. Many of your readers will quickly scan the text, and then spend more time looking at your graphs.

Selecting the appropriate kind of graph depends on the nature of the data and the specific relationships or patterns you aim to highlight. These are the main kinds of graphs used for reporting quantitative research.

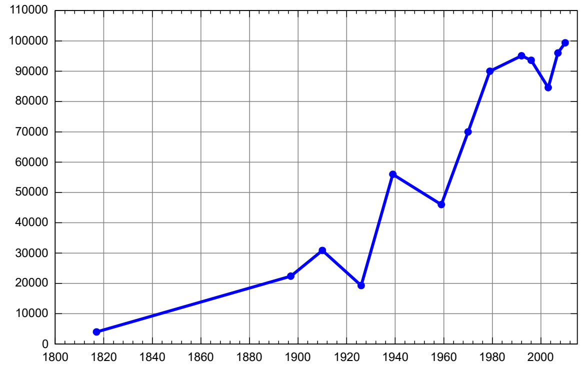
Bar Charts
These are useful for comparing quantities across different categories.[i]



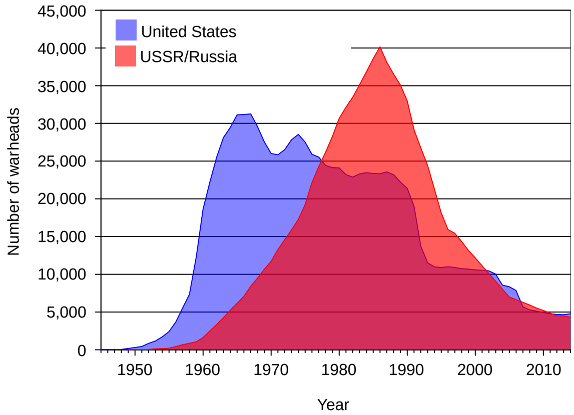
Line Graphs
Best for showing trends over time or relationships between variables.[ii]



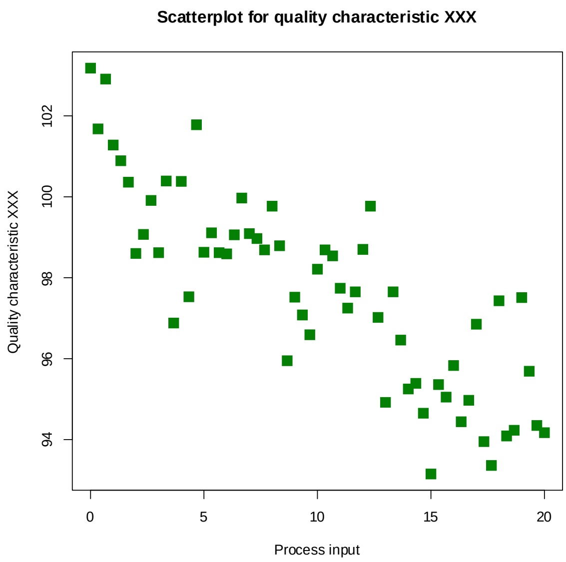
Another line graph[iii]



Area Graphs[iv]
Similar to line graphs but with the area below the line filled, emphasizing the magnitude of change over time.

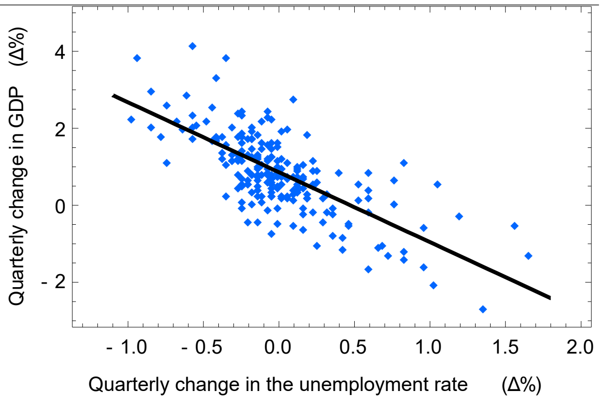


Scatter Plot (Two dimentions)
Illustrate the relationship between two continuous variables, helping to identify correlations.[v]

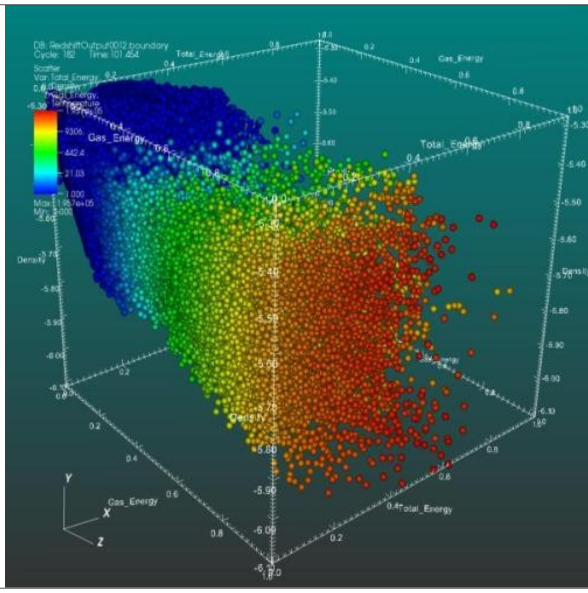


Scatter Plot showing best fit
Data does not necessary follow a neat pattern, but a scatter plot can make it easy to see trends.[vi]

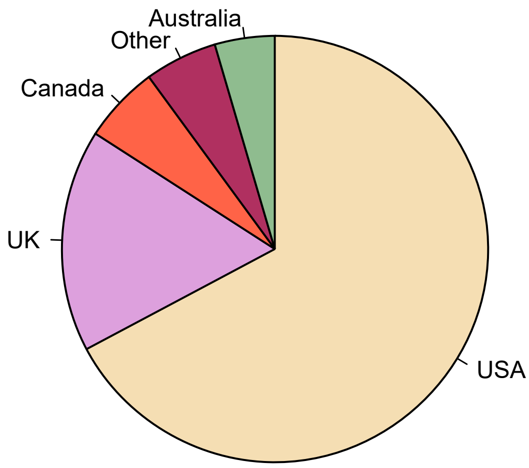
Real data is usually a little messy. If you read an article and the data looks perfectly linear, you should suspect that the data has been manipulated.



Scatter Plots (Three dimentions)
Illustrates the relationship between three continuous variables.[vii]



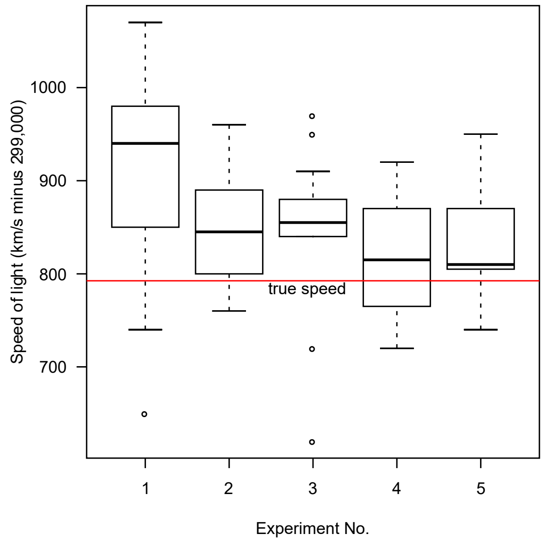
Pie Charts
Represent parts of a whole, suitable for showing percentage distributions.



Pie chart of populations of English native speakers[viii]

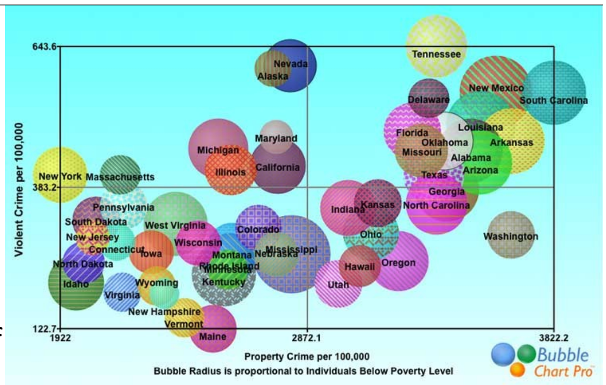
Box Plots

Provide a summary of a variable's distribution, including median, quartiles, and outliers.
This example shows the locality, spread and skewness groups of numerical data through their quartiles.[ix]



Bubble Charts

Extend scatter plots by adding a third variable represented by the size of the bubbles.
This example shows the relationship between poverty and violent and property crime rates by US state. Larger bubbles indicate a higher percentage of state residents at or below the poverty level. It suggest that states with higher crime rates have higher percentages of people living below the poverty level.[x]



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Journal Articles and Dissertations

Some methods might not work for a dissertation. First, first, surveys are data colletion methods and probably won't work unless you need lot of complx data and have a complex analysis procedure for a very specific purpose. (It is more likely that you will use surveys as data collection for another method.) Second, longitudinal studies are not feasible if you need to collect data over several years and your institution requires you to devise your own tools and collect your own data.

Otherwise, the methodology section in a PhD dissertation is typically more complex than that in a short journal article because they differ in depth, scope, and rigor.

Comprehensiveness and Detail

Due to space constraints, the methodology section in a journal article is typically brief and focuses on the essentials, often referring readers to supplementary materials or previous studies for more details.

In a dissertation, the methodology chapter must include extensive detail on research design, data collection methods, sampling strategies, instrumentation, and data analysis techniques. It also often includes longer sections on assumptions, limitations, and ethical considerations.

Theoretical and Methodological Justification

A journal article usually gives a more concise justification, and assumes readers have background knowledge.

In contrast, a dissertation requires a strong theoretical framework and a justification for every methodological choice. For instance, the student needs to say or how the sampling method aligns with the research question, and why a specific statistical test was chosen. (Some supervisors might also require the student to give reasons why one test is preferable to other tests.)

Multiple Methods or Advanced Techniques

Journal articles often focus on a single study or experiment with one primary method or statistical model.

In a PhD dissertation, the methodology may involve multiple phases, such as pilot studies, more extensive data collection, or a combination of quantitative and qualitative methods (mixed methods research). Additionally, advanced statistical models like structural equation modeling (SEM) or hierarchical linear modeling (HLM) are more common.

Pilot Studies and Instrument Development

Space limitations for journal articles mean that only the final version of the instrument and key validation results are typically shared.

PhD students often create new instruments (e.g., surveys, tests). Consequently, the dissertation includes details about instrument development, validity testing, and reliability analysis (e.g., Cronbach's alpha, factor analysis).

Reproducibility and Transparency

Journal articles often focus on results and implications, with detailed methodological materials available in supplementary files.

In a dissertation, the methodology must be detailed enough for another researcher to replicate the study step-by-step. This often includes appendices with the full survey, codebooks, and data analysis scripts.

Ethical Considerations and Research Governance

In a journal article, ethical considerations are usually summarized in a brief statement. Dissertations, however, might have a dedicated section on ethical approval, informed consent procedures, risk analysis, and how participant confidentiality was maintained.

Data Analysis and Interpretation

In a journal article, data analysis is more streamlined, focusing on the results most relevant to the hypothesis. This contrasts with a dissertation, where the analysis often includes exploratory data analysis (EDA), assumption testing, and detailed discussions of effect sizes, confidence intervals, and post hoc analyses. It may also include a critique of the chosen methodology.

Task

For this task, you will need a journal article and a dissertation that both use quantitative methods. (Your instructor might provide them for you or ask you to find your own.)

Compare the research methods in the journal and the dissertation.

1. In what specific ways are they similar?
2. In what specific ways are they different?

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At Doctoral Level

Some quantitative research designs are too simple for doctoral research, and this chapter is designed to help doctoral students and supervisors identify quantitative research designs that are commonly judged as insufficient for PhD-level work. Each department and each supervisor might set their own criteria, so this can only be a general guide.

The focus is not on statistical difficulty, but on scholarly depth, theoretical contribution, and methodological rigor. Understanding these distinctions early can prevent costly redesigns later in the doctoral journey. The expectation for a Ph.D. is to make a significant, original contribution to the body of knowledge, which usually requires a more advanced research design capable of explaining "why" or "how" phenomena occur.

In doctoral research, simplicity is not synonymous with clarity or elegance. Being “too simple” does not imply that a study is easy to understand or poorly executed. A study is considered too simple when it lacks originality, theoretical engagement, or explanatory power. Doctoral research is expected to contribute new knowledge, not merely apply established methods to familiar problems without extension or critique.

Descriptive-Only Studies

Descriptive studies summarize data using counts, percentages, or averages. While such studies are valuable for needs analyses or institutional reporting, they rarely meet doctoral standards on their own.

Descriptive research designs aim only to describe a phenomenon, population, or situation by answering “what, “where,” “when,” and “how” questions, without investigating underlying causes. Examples include simple surveys to determine frequencies or a single case study analysis. While valuable as a preliminary step to form hypotheses, a purely descriptive study is typically not considered robust enough for a doctoral dissertation on its own because it offers a surface-level understanding and cannot establish cause-and-effect relationships.

Purely descriptive studies focus on reporting only what exists, without attempting to explain relationships, mechanisms, or implications. These studies typically rely on frequencies, percentages, means, or simple summaries of survey data. While such studies may be useful for institutional reporting or exploratory purposes, they do not meet doctoral expectations because they lack hypothesis testing, theory engagement, and explanatory ambition. Doctoral research must move beyond description to explanation, interpretation, and contribution.

For example, a survey reporting teachers’ attitudes toward online learning using percentages and mean scores only would be inadequate. The supervisor might comment: “This study tells us what respondents think, but not why they think it, how attitudes are formed, or what theoretical framework explains these patterns. At PhD level, description must lead to explanation."

One-Group Pretest-Post-test Designs

In this common "pre-experimental" design, a single group is measured before and after a treatment. Because there is no control group, it is impossible to prove causality or rule out external factors like maturation or history (contextual events occurring during the study).

Simple Case Studies

Collecting data from only one or a few research subjects (case series) is often deemed too limited for the statistical validity required at this level.

Basic Cross-Sectional Surveys

While common, a simple "one-shot" survey that only measures variables at a single point in time is often considered "cheap and simple". Without advanced modeling (like Multiple Regression or Structural Equation Modeling), these may lack the required depth.

Simple Group Comparisons Without Theory

Quantitative studies that rely solely on basic group comparisons, such as independent-samples t-tests or one-way ANOVA, are often insufficient when they are not embedded within a strong theoretical framework. Comparing outcomes between two or more groups without addressing underlying mechanisms, contextual factors, or theoretical implications results in analytically shallow work. At the doctoral level, such analyses are only acceptable when they form part of a broader, theory-driven research design. Basic comparisons such as t-tests or ANOVA can be appropriate statistical tools, but they are insufficient when used in isolation.

For example, it would be inadequate to comparing test scores of male and female students using a t-test, with no theoretical discussion of gender, learning context, or sociocultural factors. The supervisor might comments: "The statistics are correct, but the research question is underdeveloped. Doctoral research should interrogate mechanisms, not just differences."

Replication Without Extension

Replication plays a crucial role in science, yet replication alone rarely satisfies doctoral originality requirements.

Replication studies repeat existing research designs using similar variables and methods. While replication is essential for scientific integrity, replication alone rarely satisfies doctoral originality requirements. A PhD dissertation must demonstrate novelty through theoretical extension, methodological refinement, or testing of boundary conditions. Simply reproducing prior findings with a new sample adds data but does not substantially advance knowledge.

For example, it would be inadequate to repeat a published regression study on student motivation using the same variables with a different cohort. The supervisor might comment: "You need to explain what this replication adds. Are you testing boundary conditions, challenging assumptions, or extending theory? If not, the contribution is limited."

Basic Correlational Designs

Simple correlational studies identify associations but do not explain causal pathways. Studies that report simple correlations between variables are frequently considered too weak for doctoral research. Doctoral-level quantitative research is expected to address explanatory questions, often through advanced modeling, mediation analysis, longitudinal data, or causal inference strategies.

These studies examine the relationship between variables without manipulating any of them to determine the strength and direction of the association. The primary limitation for doctoral work is that correlation does not imply causation, and there may be unaccounted for third variables influencing the results. A dissertation solely based on simple correlation often struggles to provide conclusive, in-depth explanations for why a relationship exists, which is a key requirement for a terminal degree.

For example it would be inadequate to report correlations between study time and academic achievement. The supervisor might comment: "At doctoral level, correlation is a starting point, not an endpoint. You must address directionality, mediation, or underlying processes."

Mechanical Use of Regression Models

Regression analysis becomes problematic when applied uncritically. Regression analysis is a powerful tool, but its uncritical or mechanical application undermines doctoral quality. Studies that rely on standard linear regression using obvious demographic predictors, without theoretical justification or model innovation, lack depth. Doctoral research must demonstrate thoughtful model construction, interrogation of assumptions, exploration of interactions or hierarchical structures, and alignment with theoretical propositions.

For example, it would be inadequate to predict academic performance using age, gender, and socioeconomic status without theoretical justification. The supervisor might comment: "Regression is not a magic solution. Explain why each variable matters theoretically and explore interactions or alternative models."

Weak Measurement and Instrumentation

Poor measurement undermines even sophisticated analysis. Quantitative studies that use poorly designed or unvalidated instruments are particularly problematic at the doctoral level. Custom-made surveys without evidence of reliability or validity compromise the credibility of findings. Doctoral research is expected to demonstrate rigorous measurement practices, including construct definition, psychometric evaluation, and appropriate handling of measurement error. Instrument development or validation can itself be a doctoral contribution, but only when conducted systematically and rigorously.

For example, it would be inadequate to use a self-developed motivation questionnaire without reliability or validity testing. The supervisor might comment: "Measurement quality is foundational. Without evidence of validity, your findings cannot be trusted, regardless of statistical technique."

Pre-Experimental Designs

These are the simplest form of experimental research designs, often involving a single group observed after some treatment or agent is applied. They lack control groups and/or random assignment, making them highly susceptible to various biases and alternate explanations for the results, meaning they cannot establish a clear cause-and-effect relationship.

They are often rejected fro the following reasons:

- They lack of internal validity. Simplistic designs are highly vulnerable to bias and confounding variables, meaning they cannot reliably answer why or how a phenomenon occurs.
- They lack the ability to generalize. Doctoral work must contribute new, reliable knowledge to the field. Descriptive-only data from a small or non-random sample cannot be statistically projected onto a broader population.
- They have minimal explanatory power. Using too few variables (underfitting) can lead to a model that misses important predictors, resulting in a project with little scientific weight.

What Makes Quantitative Research Doctoral-Level

Doctoral research is expected to move beyond mere description or association to provide rigorous, theoretically grounded explanations. Doctoral-level quantitative research typically involves theory-driven model testing, methodological innovation, complex data structures, causal inference, or rigorous measurement development. Statistical complexity alone is insufficient; the defining feature is contribution to knowledge.

A Guiding Principle for Students and Supervisors

If a study could reasonably be completed and defended in a master's program without major redesign, it is likely too simple for a PhD dissertation. Supervisors should challenge students to articulate clearly what is new, why it matters, and how the methodology supports that contribution.

Doctoral research is expected to move beyond mere description or association to provide rigorous, theoretically grounded explanations. Preferred quantitative designs for a Ph.D. often include:

- Explanatory or Causal Research Designs serve a higher purpose in academic research, as they aim to answer "why" and "how" questions.
- True Experimental Designs involve random assignment to control and experimental groups and manipulation of variables, allowing for the determination of cause-and-effect relationships.
- Quasi-Experimental Designs lack random assignment, but employ interventions and control measures to infer causality in natural settings where true experiments are not feasible.
- Predictive Correlational Designs/Complex Statistical Models are more complex forms of correlational analysis (such as multiple regression or structural equation modeling) that test more sophisticated theoretical models and make robust predictions.

How to Add Necessary Complexity

To elevate these designs, doctoral candidates often:

- Transition from descriptive to inferential. Use techniques like ANOVA, t-tests, or Generalized Linear Models to find significant differences between groups.
- Use advanced modeling. Incorporate mediation/moderation analysis or longitudinal data (collecting data over multiple time points) to strengthen causal claims.
- Adopt quasi-experimental designs. If true randomization is impossible, using a control group (even without random assignment) significantly increases the study's rigor.

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Checking the Definitions

Statisticians have created hundreds of different kinds of statistical tests, and many have been mentioned in the pages above. You might find that some explanations in the reference books are quite technical, and most tests have a formula but you probably don't need to understand it if a computer will do your calculations for you.

Your task

1. Define each of these simply and briefly in a way that will be useful for you.
2. Say what each test does.
3. Say when to use it.
4. Say how to avoid any common errors and misuse.

Here's the list:

1. ANCOVA
2. ANOVA
3. Chi-Square Test
4. Cohen's d
5. Confusion Matrix
6. Construct Validity
7. Cronbach's Alpha
8. Decision Trees/Random Forest
9. Growth Curve Modeling
10. k-fold cross-validation
11. Kolmogorov-Smirnov
12. Kruskal-Wallis
13. Linear Regression
14. Logistic Regression
15. Mann-Kendall test
16. Mann-Whitney U test
17. Mean Squared Error (MSE)
18. p-value:
19. Pearson's Correlation (r)
20. Pearson's Correlation Coefficient (r)
21. Pearson' coeeficient of skewnesss
22. R^2 or Adjusted R^2 * (for regression models)
23. Regression
24. Shapiro-Wilk
25. Spearman's Rank-Order Correlation (ρ)
26. Spearman's Rho (ρ):
27. t-test
28. Area Under the ROC Curve (AUC)
29. Z-test

Appendix

Software for Quantitative Research

You will need specialized software to process your data. Software programs vary greatly, and do different things. Some are free while others are not. Some require coding skills while others do not.

The trend is that people find the one that suits them best, learn to use it, and then don't use anything else unless they have no choice. Otherwise, here are my suggestions on how to choose which software to use:

1. Your supervisor will give a recommendation. It might be either general advice or a specific program.
2. Will it do what you need?
   a. An easy-to-use menu-driven program might be enough.
   b. You might need to learn how to write scripts and command lines or something more complex.
   c. What are your long-term goals? If you plan to do more quantitative research in the future, it might be worth learning a more difficult package that is more powerful.
   d. If your finances are a factor, is it free?
   e. Does it do graphs?
   f. Expect questions in your dissertation defense:
      i. Will you be able to explain what you did and why?
      ii. Will you be able to explain your choices and give your reasons?

g. How much support is available to you? How helpful is the manual? Does YouTube have tutorials?

Note. Whenever you use software for data analysis, report its name and version in the text.

G*Power

- **Purpose**: Calculates statistical power and sample size requirements.
- **How to Use**: Input effect size, desired power level (e.g., 0.8), and alpha level to determine the minimum sample size.

Social Science Statistics (SocSciStats)

- **Purpose**: Offers a suite of online tools for common statistical tests.
- **How to Use**: Access their website, input data, and choose the appropriate test (e.g., t-tests, chi-square).

SPSS

- **Purpose**: Comprehensive software for data management and statistical analysis.

- **How to Use**: Import datasets, perform analyses (e.g., ANOVA, regression), and visualize results with graphs.

MATLAB

- **Purpose**: Advanced software for numerical computation and algorithm development.
- **How to Use**: Write scripts to perform custom analyses, ideal for large datasets or complex modeling.

R

R is free but requires command lines and programming

Other options

AMOS
Eviews (for time series analysis and econometrics)
Gretl
HistCite
HLM7
InVivo
JASP
JMP
Minitab
Qualtrics
RStudio
SAS
SmartPLS
Stata
Systat
Thelightbulb.ai
Tibco's Statistica

See also XGBoost for predictive machine learning (https://xgboost.ai/)

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i By RCraig09 - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=103611926

ii By Urocyon - Self-created SVG verson of Image:ScientificGraphSpeedVsTime.jpeg, using en:Image:Netscape-navigator-usage-data.svg as a template. Both sources are in the public domain., Public Domain, https://commons.wikimedia.org/w/index.php?curid=2225468

iii By Artem Topchiy (user Art-top) using Gnuplot., CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=9931350

iv Created by Fastfission first by mapping the lines using OpenOffice.org's Calc program, then exporting a graph to SVG, and the performing substantial aesthetic modifications in Inkscape. - Own workSource data from: Robert S. Norris and Hans M. Kristensen, "Global nuclear stockpiles, 1945-2006," Bulletin of the Atomic Scientists 62, no. 4 (July/August 2006), 64-66. Online at http://thebulletin.metapress.com/content/c4120650912x74k7/fulltext.pdf, Public Domain, https://commons.wikimedia.org/w/index.php?curid=1514245

[v] By DanielPenfield - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=9402369

[vi] By Stpasha - Own work, Public Domain, https://commons.wikimedia.org/w/index.php?curid=7388037

[vii] By UCRL - Visualizations that have been created with VisIt. at wci.llnl.gov, Public Domain, https://commons.wikimedia.org/w/index.php?curid=4358059

[viii] M. W. Toews - Own work, data from English dialects1997.png, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=2377248

[ix] By User:Schutz - Own work, Public Domain, https://commons.wikimedia.org/w/index.php?curid=1501411. Adapted from C., Dutoit, S. H. (2012). *Graphical exploratory data analysis*. Springer. ISBN 978-1-4612-9371-2. OCLC 1019645745.

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