Research Methodology

Research Designs

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Outline

- Study design
- Observational study
- Sampling for quantitative studies
- Sample size in quantitative studies
- Experimental, quasi-experimental, and ex post facto designs
- Strategies for analyzing quantitative data
- Threats to validity

Study design

- The study type may dictate certain research designs.
- More commonly, the ***study objectives*** can be achieved through a number of ***alternative designs***.
- Researchers have to select the ***most appropriate*** and ***most feasible design***.
- The ***type of research design*** chosen depends on:
  - the type of **problem**;
  - the **knowledge** already available about the problem; and
  - the **resources** available for the study.

Study design …

- Generally, there are two main categories of research design:
  - observational study, and
  - experimental or intervention study.
- In the ***observational study***,
  - the researchers stand apart from events taking place in the study.
  - They *simply* observe and record.
- In the ***experimental or intervention*** study,
  - the researches introduce an intervention and
  - observe the events which take place in the study.

Observational studies

- An observational study may be
  - exploratory,
  - descriptive or
  - analytical.
- An exploratory study
  - is a small-scale study of relatively ***short duration***,
  - is carried out ***when little is known*** about a situation or a problem.
  - If the problem and its contributing factors are not well defined,
    - it is always advisable to do ***an exploratory study*** before embarking on a large-scale ***descriptive or analytic study***.

Observational studies …

- *S*mall-scale studies may be called
  - ***exploratory*** **case studies** if they lead to *plausible assumptions* about the causes of the problem and
  - ***explanatory*** **case studies** if they provide *sufficient explanations* to take action.
- A descriptive study is an observational study that simply describes the distribution of a characteristic.
- An analytical study (correlation in some disciplines)
  - is an observational study that describes associations and
  - analyze them for possible ***cause*** and ***effect***.

Observational studies …

- An observational study may be
  - cross-sectional or
  - longitudinal.
- In cross-sectional study, measurements are made on a single occasion.
- In a longitudinal study, measurements are made over a period of time.
- A longitudinal observational study may be
  - retrospective or
  - prospective
- In a retrospective study, the researchers study present and past events.
  - E.g., start from the disease and determine exposure
- In a longitudinal prospective study, the researchers follow subjects for future events.
  - E.g., start with the exposure and determine frequency of disease

Sampling for quantitative studies

"A sample is a representative of the population under study. "

- ***Sampling is the process of selecting a number of study units from a defined study population.***
- Often research focuses on a large population that, for practical reasons, it is only possible to include some of its members in the investigation.
- You then have to draw a sample from the total population.
- In such cases you must consider the following questions:
  - What is the study population you are interested in from which we want to draw a sample?
  - How many subjects do you need in your sample?
  - How will these subjects be selected?

Sampling for quantitative studies …

- The key reason for being concerned with sampling is that of ***validity***—the extent to which
  - the ***interpretations*** of the results of the study follow from the study itself and
  - results may be ***generalized*** to other situations with other people or situation.
- Sampling is critical to ***external validity*** ***(or induction)***—
  - the extent to which findings of a study can be generalized to people or situations other than those observed in the study.
- To generalize validly the findings from a sample to some defined population requires that
  - the sample has been drawn from that population according to one of several ***probability*** sampling plans.

Sampling for quantitative studies …

- Examples of probability sampling
  - Simple random sampling
  - Systematic sampling
  - Stratified sampling
  - Cluster sampling
  - Multistage sampling

Sampling for quantitative studies …

- Simple random sampling
  - The guiding principle behind this technique is that
    - *each element must have an equal and nonzero chance of being selected.*
  - This can be achieved
    - by applying a table of random numbers or
    - a computer generated random numbers to a ***numbered sampling frame***.
  - The product of this technique is a sample determined entirely by chance.
  - Random selection ***does not always produce*** a sample that is representative of the population.

Sampling for quantitative studies …

- Simple random sampling …
  - Imagine, for example, a sampling frame comprising 10,000 people.
  - Furthermore, consider that altitude is a critical variable, and that the composition of the sampling frame is as follows:
    - 1,500 are from high altitude ;
    - 7,500 are from medium altitude, and
    - 1,000 are from low altitude.
  - You are going to select a sample of 500 people from this sampling frame using a simple random sampling technique.
  - Unfortunately, the simple random selection process may or may not yield a sample that has equivalent altitudinal proportions as the sampling frame.
  - Disproportionate numbers of each altitudinal category may be selected.

Sampling for quantitative studies …

- Systematic sampling
  - This technique begins with selecting one element at random in the sampling frame as the starting point;
  - however, from this point onward, the rest of the sample is selected systematically by applying a predetermined interval.
  - For example, in this technique,
    - after the initial element is selected at random,
    - every "k^{th}" element will be selected (k^{th} refers to the size of the interval—the ratio of the population to sample size).

Sampling for quantitative studies …

- Systematic sampling …
  - The “kth ” element is selected
    - through the end of the sampling frame and
    - then from the beginning until a complete cycle is made back to the starting point
  - If there is ***a cyclic repetition*** in the sampling frame, systematic sampling is not recommended.

Sampling for quantitative studies …

- Stratified random sampling
  - begins with the identification of some variable, which may be related indirectly to the research question and
  - could act as ***a confounder*** (such as geography, age, income, ethnicity, gender).
  - This variable is then used to divide the sampling frame into **mutually exclusive *strata*** or subgroups.
  - Once the ***sampling frame is arranged by strata***, the sample is selected from each stratum using ***simple random sampling*** or ***systematic sampling***.
  - The sample selected within each stratum reflects ***proportionately*** the population proportions;

Sampling for quantitative studies …

- Cluster sampling
  - It may be difficult or impossible to take a simple random sample of the units of the study population at random, because ***a complete sampling frame does not exist***.
  - Logistical difficulties may also discourage random sampling techniques
    - (e.g., interviewing people who are scattered over a large area may be too time-consuming).
  - However, when a list of groupings of study units is available
    - (e.g., villages or schools) or can be easily compiled,

    a number of these groupings can be randomly selected.
  - Then all study units in the selected clusters will be included in the study.

Sampling for quantitative studies …

- Multistage sampling
  - Multistage cluster sampling is used when ***an appropriate sampling frame does not exist*** or cannot be obtained.
  - Multistage cluster sampling uses a collection of preexisting units or clusters to “stand in” for a sampling frame.
    - The first stage in the process is selecting ***a sample of clusters*** at random from the list of all known clusters.
    - The second stage consists of selecting a random sample from each cluster.

Sampling for qualitative studies

- Qualitative research methods are typically used
  - when focusing on ***a limited number of informants***,
  - whom you select *strategically* so that
  - their in-depth information will give optimal insight into an issue about which little is known.
- This is called *purposeful sampling*.

Sample size in quantitative studies

"You have to make a trade-off b/n generating a large enough sample size to make a valid generalization to the population and the many constraints that appear with increasing sample size."

- Having decided **how** to select sample, you have to determine the **sample size**.
- A research proposal should provide information & justification about sample size.
- ***It is not necessarily true that the bigger the sample, the better the study.***
- Beyond a certain point, an increase in sample size will not improve the study.
- In fact, it may do the opposite if the ***quality***
  - of the measurement or
  - data collection

  is adversely affected by the large size of the study.

Sample size in quantitative studies ...

- After a certain sample size, in general,
  - it is much better to increase the ***accuracy and richness*** of data collection (for example by
    - improving the ***training of interviewers***,
    - by ***pre-testing*** of the data collection tools or
    - by ***calibrating*** measurement devices).
  - than to increase sample size.
- Also, it is better to make extra effort to get a ***representative*** sample rather than to get a very large sample.

Sample size in quantitative studies ...

- The ***level of precision*** needed for the estimates will impact the sample size.
- Generally, the actual sample size of a study is a compromise between
  - the ***level of precision*** to be achieved,
  - the ***research budget*** and
  - any other ***operational constraints***, such as **time**

Sample size in quantitative studies ...

- In order to achieve a certain level of precision, ***the sample size*** will depend, among other things, on the following factors:
  - The ***variability of the characteristics*** being observed:
    - E.g. If the salaries of persons in a population are very different, then you would need a bigger sample in order to produce a reliable estimate.
  - The ***population size***:
    - To a certain extent, **the bigger the population, the bigger the sample** needed.
    - But once you reach a certain level, an increase in population no longer affects the sample size.

Sample size in quantitative studies ...

– The sampling and ***estimation*** methods:

- ➢ Not all sampling and estimation methods have the same level of ***efficiency***.
- ➢ You will ***need a bigger sample*** if your method is ***not*** the most efficient.
- ➢ But because of ***operational constraints*** and the ***unavailability of an adequate frame***, you cannot always use the most efficient technique.

Experimental, quasi-experimental, and ex post facto designs

- Experimental research
  - Researcher manipulates the independent variable and examines its effect on another, dependent variable
  - There are different research designs
    - Differs in the extent to which the researcher manipulates the independent variable and controls for confounding variables

  - Designs are illustrated using the following general format

Group	Time →		
Group 1			
Group 2			

Tx: Indicates that a treatment (reflecting the independent variable) is presented.
Obs: Indicates that an observation (reflecting the dependent variable) is made.
-: Indicates that nothing occurs during a particular time period.
Exp: Indicates a previous experience(an independent variable) that some participants have had and others have not; the experience has not been one that the researcher could control.

Experimental, quasi-experimental, and ex post facto designs…

- Pre-experimental design
  - It is not possible to show cause-and-effect relationships, because
    - The independent "variable" does not vary
    - Experimental and control groups are not comprised of equivalent or randomly selected individuals
  - Helpful only for forming tentative hypotheses that should be followed up with more controlled studies

Experimental, quasi-experimental, and ex post facto designs…

- Pre-experimental design…

Name of the Design	Aim of the Research	Graphic Depiction	Comments on the Design
		Pre-Experimental Designs	
1. One-shot experimental case study	To show that one event (a treatment) precedes another event (the observation)	Group / Time → Group 1 | Tx | Obs	Shows a before-and-after sequence but cannot substantiate that this is a cause-and-effect relationship.
2. One group pretest-posttest design	To show that change occurs after a treatment	Group / Time → Group 1 | Obs | Tx | Obs	Provides a measure of change but yields no conclusive results about the cause of the change.
3. Static group comparison	To show that a group receiving a treatment behaves differently than one receiving no treatment	Group / Time → Group 1 | Tx | Obs Group 2 | — | Obs	Fails to determine pretreatment equivalence of groups.

Experimental, quasi-experimental, and ex post facto designs…

- True experimental design
  - Offers a greater degree of control and, as a result, greater internal validity
  - In the first three of the four designs presented below, people or other units of study are randomly assigned to groups
  - The last one presents all treatments and any control conditions to a single group

Experimental, quasi-experimental, and ex post facto designs…

Name of the Design	*Aim of the Research*	*Graphic Depiction*	*Comments on the Design*
		True Experimental Designs	
4. Pretest-posttest control group design	To show that change occurs following, but only following, a particular treatment	Group Time → Random Assignment Group 1 | Obs | Tx | Obs Group 2 | Obs | — | Obs	Controls for many potential threats to internal validity.
5. Solomon four-group design	To investigate the possible effect of pretesting	Group Time → Random Assignment Group 1 | Obs | Tx | Obs Group 2 | Obs | — | Obs Group 3 | — | Tx | Obs Group 4 | — | — | Obs	Enables the researcher to determine how pretesting may affect the final outcome observed.
6. Posttest-only control group design	To determine the effects of a treatment when pretesting cannot or should not occur	Group Time → Random Assignment Group 1 | Tx | Obs Group 2 | — | Obs	Uses the last two groups in the Solomon four-group design; random assignment to groups is critical for maximizing group equivalence.
7. Within-subjects design	To compare the relative effects of different treatments for the same participants	Group Time → Group 1 | Tx_a | Obs_a | Tx_b | Obs_b	Useful only when effects of each treatment are temporary and localized.

Experimental, quasi-experimental, and ex post facto designs…

- Quasi-experimental design
  - Used when randomness is either impossible or impractical
  - Confounding variables are not controlled
    - Researchers cannot completely rule out some alternative explanations for the results they obtain
    - During interpretation, variables the researchers didn’t control for should be taken into consideration

Experimental, quasi-experimental, and ex post facto designs…

- Quasi-experimental design…

Name of the Design	*Aim of the Research*	*Graphic Depiction*	*Comments on the Design*
Quasi-Experimental Designs			
8. Nonrandomized control group pretest–posttest design	To show that two groups are equivalent with respect to the dependent variable prior to the treatment, thus eliminating initial group differences as an explanation for posttreatment differences	Group — Time → Group 1: Obs, Tx, Obs Group 2: Obs, —, Obs	Differs from experimental designs because test and control groups are not totally equivalent; equivalence on the pretest ensures equivalence only for variables that have specifically been measured.
9. Simple time-series experiment	To show that, for a single group, change occurs during a lengthy period only after the treatment has been administered	Group — Time → Group 1: Obs, Obs, Tx, Obs, Obs	Provides a stronger alternative to Design 2; external validity can be increased by repeating the experiment in different places under different conditions.
10. Control group, time-series design	To bolster the internal validity of the preceding design with the addition of a control group	Group — Time → Group 1: Obs, Obs, Tx, Obs, Obs Group 2: Obs, Obs, —, Obs, Obs	Involves conducting parallel series of observations for experimental and control groups.

Experimental, quasi-experimental, and ex post facto designs…

- Quasi-experimental design…

Name of the Design	Aim of the Research	Graphic Depiction	Comments on the Design
		Quasi-Experimental Designs	
11. Reversal time-series design	To show, in a single group or individual, that a treatment consistently leads to a particular effect	Group Time → Group 1 | Tx | Obs | — | Obs | Tx | Obs	Is an on-again, off-again design in which the experimental treatment is sometimes present, sometimes absent.
12. Alternating treatments design	To show, in a single group or individual, that different treatments have different effects	Group Time → Group 1 | Tx_a | Obs | — | Obs | Tx_b | Obs	Involves sequentially administering different treatments at different times and comparing their effects against the possible consequences of nontreatment.
13. Multiple baseline design	To show the effect of a treatment by initiating it at different times for different groups or individuals, or perhaps in different settings for a single individual	Group Time → Group 1 | — | Obs | Tx | Obs | Tx | Obs Group 2 | — | Obs | — | Obs | Tx | Obs	Involves tracking two or more groups or individuals over time, or tracking a single individual in two or more settings, for a lengthy period of time, as well as initiating the treatment at different times for different groups, individuals, or settings.

Experimental, quasi-experimental, and ex post facto designs…

- Ex-post facto design
  - In many situations it is either unethical or impossible to manipulate certain variables in order to investigate their potential influence on other variables
  - Example
    - Infecting people with a potentially deadly new virus, ask parents to abuse their children, or modify a person's personality
  - Provides alternative means by which a researcher can investigate the extent to which such specific independent variables may possibly affect the dependent variables of interest
  - Literally means "after the fact"
  - A researcher identifies *events that have already occurred or conditions that are already present* and then collects data to investigate a possible relationship between these factors and subsequent characteristics or behaviors

Experimental, quasi-experimental, and ex post facto designs…

- Ex-post facto design…
  - Ex-post facto design vs correlational or experimental designs
    - Similarity
      - Both ex-post facto and correlational designs involve looking at existing circumstances
      - Both ex-post facto and experimental researches clearly identify independent and dependent variables
    - Differences
      - Ex-post fact designs do not involve direct manipulation of the independent variable – The presumed "cause" has already occurred
      - The researcher cannot draw firm conclusion about cause and effect
        - » Experimenter cannot control for confounding variables that may provide alternative explanations for any group differences observed

Experimental, quasi-experimental, and ex post facto designs…

- Ex-post facto design…

Name of the Design	Aim of the Research	Graphic Depiction	Comments on the Design
		Ex Post Facto Designs	
14. Simple ex post facto design	To show the possible effects of an experience that occurred, or a condition that was present, prior to the investigation	Group / Time → Group 1 | Exp | Obs Group 2 | — | Obs	May show a difference between groups but does not conclusively demonstrate that the difference is due to the prior experience/condition in question.

Experimental, quasi-experimental, and ex post facto designs…

- Factorial design
  - Used to study effects of two or more independent variables in a single study

<table>
<tr><th>Name of the Design</th><th>Aim of the Research</th><th>Graphic Depiction</th><th>Comments on the Design</th></tr>
<tr><td colspan="4">Factorial Designs</td></tr>
<tr><td>15. Two-factor experimental design</td><td>To study the effects of two experimenter-manipulated variables and their possible interaction</td><td>
<table>
<tr><th></th><th>Group</th><th>Time →</th><th></th><th></th></tr>
<tr><td rowspan="4">Random Assignment</td><td>Group 1</td><td>Tx_1</td><td>Tx_2</td><td>Obs</td></tr>
<tr><td>Group 2</td><td>Tx_1</td><td>—</td><td>Obs</td></tr>
<tr><td>Group 3</td><td>—</td><td>Tx_2</td><td>Obs</td></tr>
<tr><td>Group 4</td><td>—</td><td>—</td><td>Obs</td></tr>
</table>
</td><td>Requires a larger sample size than two-group studies; random assignment to treatments is essential.</td></tr>
<tr><td>16. Combined experimental and ex post facto design</td><td>To study the possible effects of an experimenter-manipulated variable, a previously existing condition, and the interaction between the two</td><td>
<table>
<tr><th>Group</th><th>Time →</th><th></th><th></th><th></th><th></th></tr>
<tr><td rowspan="2">Group 1</td><td rowspan="2">Exp_a</td><td rowspan="2">Random Assign-ment</td><td>Group 1a</td><td>Tx_a</td><td>Obs</td></tr>
<tr><td>Group 1b</td><td>Tx_b</td><td>Obs</td></tr>
<tr><td rowspan="2">Group 2</td><td rowspan="2">Exp_b</td><td rowspan="2">Random Assign-ment</td><td>Group 2a</td><td>Tx_a</td><td>Obs</td></tr>
<tr><td>Group 2b</td><td>Tx_b</td><td>Obs</td></tr>
</table>
</td><td>Requires a larger sample size than two-group studies; random assignment to the experimenter-manipulated variable is essential.</td></tr>
</table>

Experimental, quasi-experimental, and ex post facto designs…

- Reading assignment
  - Paul D. Leedy and Jeanne Ellis Ormrod, Practical Research: Planning and Design, 10th edition, Chapter 9

- Test
  - Read about **threats to validity** in research

Strategies for analyzing quantitative data

- *Numbers are meaningless unless we analyze and interpret them in order to reveal the truth that lies beneath them*
  - With **statistics** we can
    - summarize large number of data sets
    - make prediction about future trends
    - determine when two different experimental treatments have led to significantly different outcomes
- Statistics
  - A group of computational procedures that enable us to find patterns and meaning in numerical data
  - Are among the most powerful tools in a researcher's toolbox
  - Provide a means through which numerical data can be made more meaningful
    - Help the researcher see their nature and better understand their interrelationships
  - Question of statistics is the same as what the researcher asks
    - What do the data mean?
    - What message do they communicate?

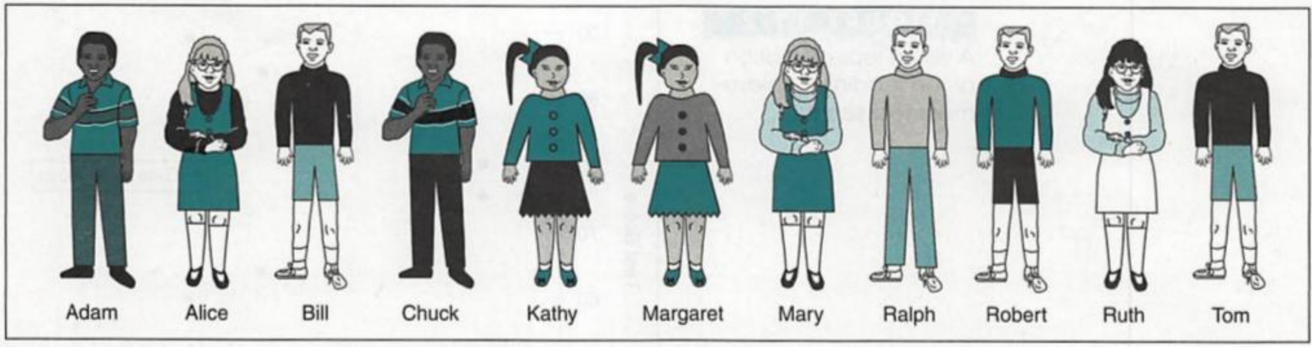
Strategies for analyzing quantitative data…

- Exploring and organizing data set
  - Before making a single computation,
    - look closely at your data and explore various ways of organizing them
    - look for patterns in the numbers
  - Example
    - Scores on a reading achievement test for 11 children

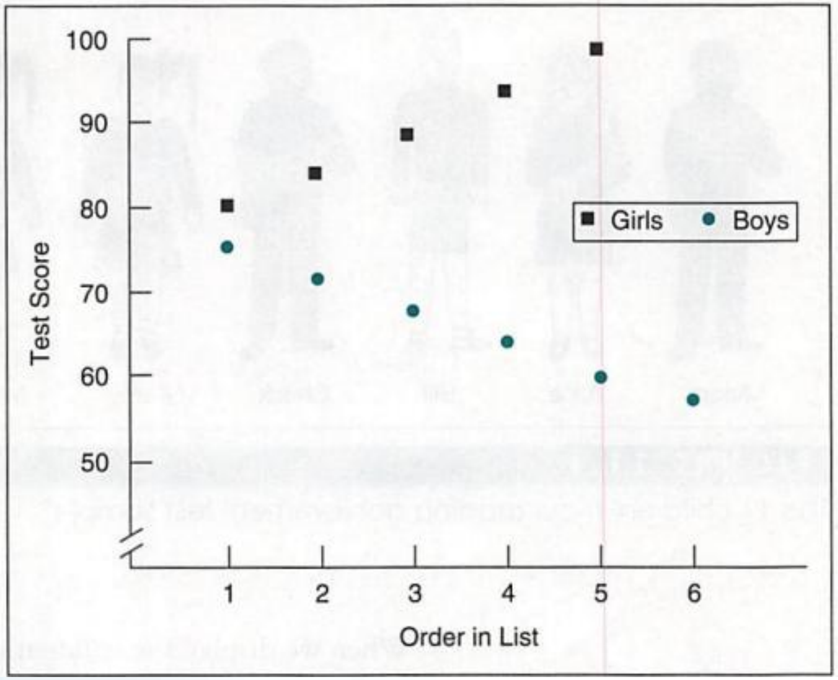
      Ruch, 96; Robert, 60; Chuck, 68; Margaret, 88; Tom, 56; Mary, 92; Ralph, 64; Bill, 72; Alice, 80; Adam, 76; Kathy, 84
    - What do you see?

Strategies for analyzing quantitative data…

- Exploring and organizing data set…
  - Example…



Girls		*Boys*	
Alice	80	Adam	76
Kathy	84	Bill	72
Margaret	88	Chuck	68
Mary	92	Ralph	64
Ruth	96	Robert	60
		Tom	56



Strategies for analyzing quantitative data…

- Exploring and organizing data set…
  - Whatever we have observed may have no relevance whatsoever for our project, but because it represents *dynamics within the data*, it is important that we see it
  - How the researcher prepares the data for inspection or interpretation will affect the meaning that those data reveal
  - Every researcher should be able to provide a clear, logical rationale for the procedure used to arrange and organize the data

Strategies for analyzing quantitative data…

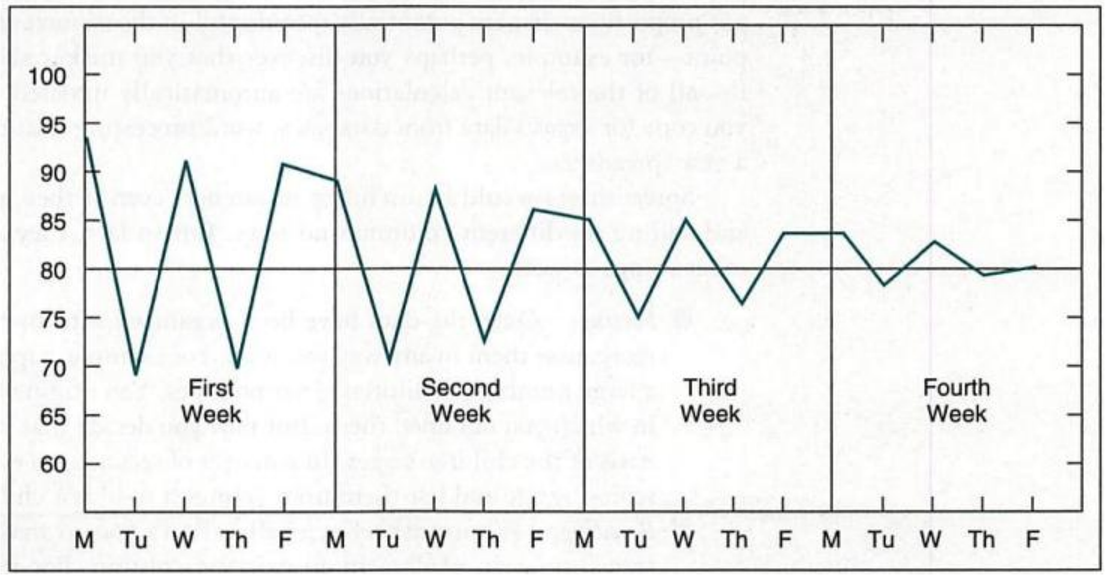
- Organizing data to make them easier to think about and interpret
  - The human mind can think about only so much information at one time
  - The researcher usually needs to organize the data in one or more ways to make them easier to inspect and think about
  - Example
    - Joe's February quiz grades: 92, 69, 91, 70, 90, 89, 72, 87, 73, 86, 85, 75, 84, 76, 83, 83, 77, 81, 78, 79
    - Two dimensional table organized by weeks and days

Grade Record for February

	Monday	*Tuesday*	*Wednesday*	*Thursday*	*Friday*
First week	92	69	91	70	90
Second week	89	72	87	73	86
Third week	85	75	84	76	83
Fourth week	83	77	81	78	79

Strategies for analyzing quantitative data…

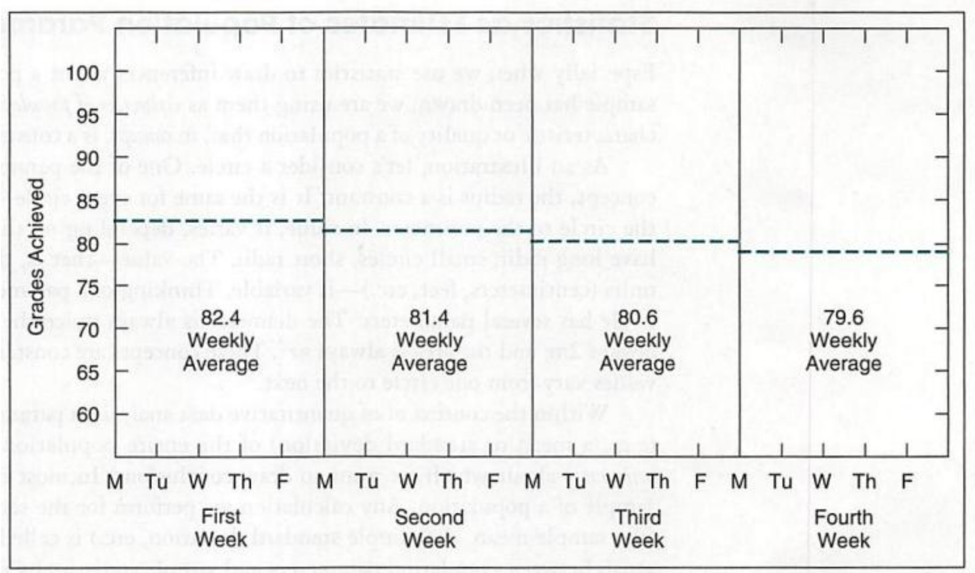
- Organizing data to make them easier to think about and interpret…
  - Example…
    - Simple line graph representation of Joe's grades



  - Graphing data is often quite useful for revealing patterns in a data set

Strategies for analyzing quantitative data…

- Organizing data to make them easier to think about and interpret…
  - Example…
    - Summarize the data using a statistics known as a mean



  - The means tell us nothing about how consistent or inconsistent Joe's grades are in any given week
  - Looking at data in only one way yields an incomplete view of those data and thus provides only a portion of the meaning those data hold

Strategies for analyzing quantitative data…

- Functions of statistics
  - Descriptive statistics
    - Describe how the data looks like
      - Where the center of midpoint is, how broadly they are spread, how closely two or more variables within the data are intercorrelated,…
  - Inferential statistics
    - Allows to draw inferences about large populations by collecting data on relatively small samples
    - Involve using a small sample of a population and then estimating the characteristics of the larger population from which the sample has been drawn
    - Provide a way of helping us make reasonable guesses about a large, unknown population by examining a small sample that is known
    - Allow us to test hypotheses regarding what is true for that large population
    - Note
      - The inference may be inaccurate due to small sample size

Strategies for analyzing quantitative data…

- Population parameter
  - A characteristic or quality of a population that, in concept, is a constant; however, its value is variable
  - Within the context of quantitative data analysis,
    - A parameter is a particular characteristic (e.g., a mean or standard deviation) of the entire population about which we want to draw conclusions
    - Any calculation we perform for the sample rather than the population (the sample mean, the sample standard deviation, etc.) is called a statistic
  - Population parameters and sample statistics are represented using different symbols

	The Symbol Used to Designate the Factor	
The Factor in Question	*Population Parameter*	*Sample Statistic*
The mean	μ	$\bar{M}$ or X
The standard deviation	σ	*s* or *SD*
Proportion or probability	*P*	*p*
Number or total	*N*	*n*

Note: The symbol μ is the lowercase form of the Greek letter *mu*. The symbol σ is the lowercase form of the Greek letter *sigma*.

Strategies for analyzing quantitative data…

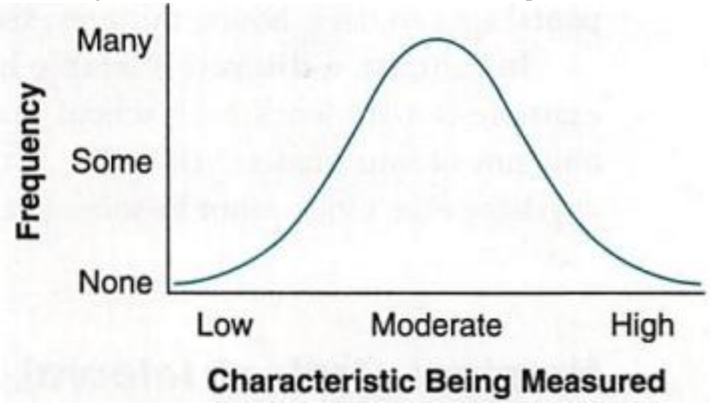
- Nature of data
  - – Different statistics are suitable for different kinds of data
  - – One has to consider whether the data
    - Have been collected for a single group or, instead, for two or more groups
    - Involve continuous or discrete variables
      - – Example: Age vs year of study in university
    - Represent nominal, ordinal, interval, or ratio scales
      - – Nominal data
        - » Are those for which numbers are used only to identify different categories of people, objects, or other entities;
        - » They do not reflect a particular quantity or degree of something

Strategies for analyzing quantitative data…

- Nature of data…
  - One has to consider whether the data …
    - Represent nominal, ordinal, interval, or ratio scales…
      - Ordinal data
        - » Are those for which the assigned numbers reflect an order or sequence
        - » They tell us the degree to which people, objects, or other entities have a certain quality or characteristic (a variable) of interest
        - » They do not, however, tell us anything about how great the differences are between the people, objects, or other entities
        - » Example: Rank of students
      - Interval data
        - » Reflect equal units of measurement
        - » The numbers reflect differences in degree or amount and also tell us how much difference exists in the characteristic being measured
        - » Limitation
          - A value of zero (0) does not necessarily reflect a complete lack of the characteristic being measured
          - Example, it is sometimes possible to get an IQ score of 0, but such a score does not mean that a person has no intelligence whatsoever

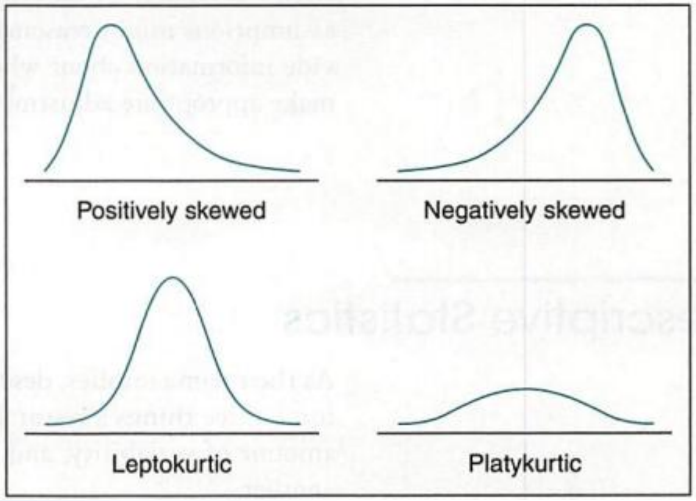
Strategies for analyzing quantitative data…

- Nature of data…
  - One has to consider whether the data …
    - Represent nominal, ordinal, interval, or ratio scales…
      - Ratio data
        - » Similar to interval data but have an additional feature: a true zero point
        - » The numbers reflect equal intervals between values for the characteristic being measured, and a value of 0 tells us that there is a complete absence of that characteristic
    - Normal and non-normal distribution
      - Numerous theorists have proposed that many characteristics of living populations reflect a particular pattern



Strategies for analyzing quantitative data…

- Nature of data…
  - One has to consider whether the data …
    - Normal and non-normal distribution…
      - The curve is a constant, it is always bell-shaped
      - The mean is not always the same number, and the overall shape may be more broadly spread or more compressed, depending on the situation
      - Sometimes, a variable doesn't fall in a normal distribution
        - » Example:
          - its distribution might be lopsided or skewed, or pointy or flat (Kurtosis)
      - Common departures from a normal distribution



Strategies for analyzing quantitative data…

- Nature of data…
  - One has to consider whether the data …
    - Normal and non-normal distribution…
      - Some data sets don't resemble a normal distribution or its variations
      - Example
        - » Student class rank
        - » Percentile ranks

$$\text{Percentile rank} = \frac{\text{Number of other people scoring } \textit{lower} \text{ than the person}}{\text{Total number of people in the sample}}$$

Strategies for analyzing quantitative data…

- Parametric and non-parametric statistics
  - Choice of statistical procedures must depend
    - To some degree on the nature of your data and
    - The extent to which they reflect a normal distribution
  - Parametric statistics are based on certain assumptions about the nature of the population in question
    - The data reflect an interval or ratio scale
    - The data fall in a normal distribution
      - E.g., the distribution has a central high point, and it is not seriously skewed, leptokurtic, or platykurtic
  - A violation of these assumptions give a questionable result
  - Non-parametric statistics
    - Some types of such statistics are appropriate for data that are ordinal rather than interval
    - Other types could be useful when a population is highly skewed in one direction or the other
    - Appropriate only for relatively simple analyses

Strategies for analyzing quantitative data…

- Descriptive statistics
  - Describe a body of data
  - Measures of central tendency
    - A *point of central tendency* is a point around which the data revolve, a middle number around which the data regarding a particular variable seem to hover
      - Measures of central tendency refers to techniques for finding such a point
    - Commonly used measures of central tendency
      - Mode, median and mean
    - Mode
      - is the single number or score that occurs most frequently
      - is of limited value as a measure of central tendency
        - » It does not always appear near the middle of the distribution
        - » It is not very stable from sample to sample
      - is the only appropriate measure of central tendency for nominal data

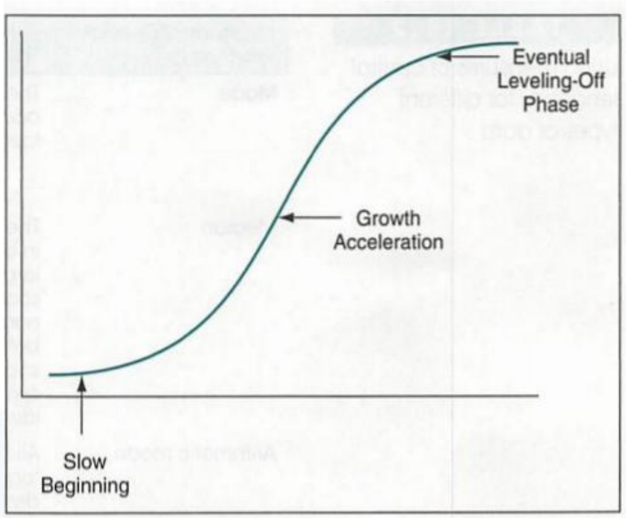
Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of central tendency…
    - Median
      - is the numerical center of a set of data, with exactly as many scores above it as below it
      - is the one precisely in the middle of the series
      - appropriate for dealing with ordinal data
      - Usually used when the researcher is dealing with a data set that is highly skewed in one direction or the other
      - Example
        - » 3 4 5 5 6 9 15 17 125
    - Mean
      - represents the single point at which the two sides of a distribution "balance"
      - is the arithmetic average of the scores within the data set
      - appropriate only for interval or ratio data
        - » It makes mathematical sense to compute an average only when the numbers reflect equal intervals along a particular scale

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of central tendency…
    - Geometric mean
      - Arithmetic mean is most appropriate when we have a normal distribution or at least a distribution that is somewhat symmetrical
      - Not all data has this nature (normal distribution)
      - Example
        - » Growth is a function of geometric progression
          - Follows an ogive curve that eventually flattens into a plateau
      - is computed by multiplying all of the scores together and then finding the Nth root of the product

$$M_g = \sqrt[N]{(X_1)(X_2)(X_3)\ldots(X_N)}$$



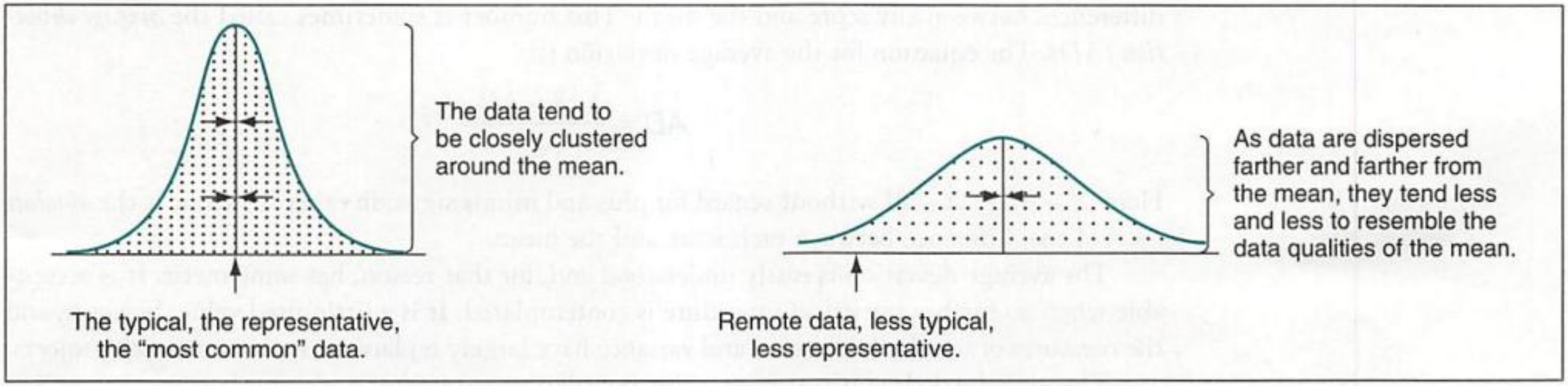
Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of central tendency…

Measure of Central Tendency	*How It Is Determined (N = number of scores)*	*Data for Which It Is Appropriate*
Mode	The most frequently occurring score is identified.	• Data on nominal, ordinal, interval, and ratio scales • Multimodal distributions (two or more modes may be identified when a distribution has multiple peaks)
Median	The scores are arranged in order from smallest to largest, and the middle score (when *N* is an odd number) or the midpoint between the two middle scores (when *N* is an even number) is identified.	• Data on ordinal, interval, and ratio scales • Data that are highly skewed
Arithmetic mean	All the scores are added together, and their sum is divided by the total number (*N*) of scores.	• Data on interval and ratio scales • Data that fall in a normal distribution
Geometric Mean	All the scores are multiplied together, and the *N*th root of their product is computed.	• Data on ratio scales • Data that fall in an ogive curve (e.g., growth data)

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of variability: dispersion and deviation
    - Central tendency is about getting the answer to “*What is the best guess?*”
    - Measures of variability focuses on answering the question “*What are the worst odds*?”
    - The more the data clusters around the point of central tendency, the greater is the probability of making a correct guess about where any particular data point lies
    - To derive meaning from data, then, it's important to determine not only their central tendency but also their spread



Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of variability: dispersion and deviation…
    - How to measure the spread?
    - Range
      - Simplest measure
      - Indicates the spread of the data from lowest to highest value

        Range = Highest score – Lowest score
      - Misleading if the extreme upper or lower limits are atypical of the other values
      - Example: numbers of children in each of ten families

        1, 3, 3, 3, 4, 4, 5, 5, 6, 15
        - » Range shows high variability, i.e., 14, but there is not much variability in the data

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of variability: dispersion and deviation…
    - Interquartile range
      - Divides the distribution into four equal parts
        - » Quartile 1 lies at a point where 25% of the members of the group are below it
        - » Quartile 2 divides the group into two equal parts and is identical to the median
        - » Quartile 3 lies at a point where 75% of the values are below it

Interquartile range = Quartile 3 - Quartile 1

      - Gives the range for the middle 50% of the cases in the distribution
      - Any researcher employing the median as a measure of central tendency should also consider the quartile deviation as a possible statistical measure of variability

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of variability: dispersion and deviation…
    - Average deviation (AD)
      - Measures how far away from the mean each piece of data is in the distribution

$$AD = \frac{\sum |X - M|}{N}$$

      - Easily understood
      - Acceptable when no further statistical procedure is contemplated

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of variability: dispersion and deviation…
    - Standard deviation
      - is a measure of variability most commonly used in statistical procedures
      - The calculation follows similar procedure as average deviation. However, instead of taking the absolute value of the score-mean difference, we square the difference

$$s = \sqrt{\frac{\Sigma(X - M)^2}{N}}$$

    - Variance

$$s^2 = \frac{\Sigma(X - M)^2}{N}$$

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of variability: dispersion and deviation…

Measure of Variability	*How It's Determined (N = number of scores)*	*Data for Which It's Appropriate*
Range	The difference between the highest and lowest scores in the distribution	• Data on ordinal, interval, and ratio scales*
Interquartile range	The difference between the 25th and 75th percentiles	• Data on ordinal, interval, and ratio scales • Especially useful for highly skewed data
Standard deviation	$s = \sqrt{\dfrac{\Sigma(X - M)^2}{N}}$	• Data on interval and ratio scales • Most appropriate for normally distributed data
Variance	$s^2 = \dfrac{\Sigma(X - M)^2}{N}$	• Data on interval and ratio scales • Most appropriate for normally distributed data • Especially useful in inferential statistical procedures (e.g., analysis of variance)

* Measures of variability are usually inappropriate for nominal data. Instead, frequencies or percentages of each number are reported.

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Standard score
    - Sometimes it is difficult to interpret a raw score
    - Example: A score of 35 on a test of extroversion
      - What does this score mean? Is it high? Low? In the middle?
      - No context to interpret the score
    - Tells us how far an individual's performance is from the mean with respect to standard deviation units
    - Z-score
      - Simplest standard score

$$z = \frac{X - M}{s}$$

      - When we calculate z-scores for an entire group, we get a distribution that has a mean of 0 and a standard deviation of 1

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Standard score …
    - Z-score
      - To convert a z-score to another scale (e.g., IQ score or Stanine)

$$\text{New standard score} = (z \times s_{new}) + M_{new}$$

Where s_{new} is standard deviation of new scale and M_{new} is mean of new scale

    - If we know the mean and standard deviation on which the scores are based, then we also know where in the distribution any particular score lies
    - Example
      - An IQ score of 70 is two standard deviations (30 points) below the mean of 100
        - » IQ scale has a mean of 100 and standard deviation of 15
    - Standard scores are also used in normalization

Strategies for analyzing quantitative data...

- Descriptive statistics...
  - Statistics related to central tendency and variability help us summarize our data
  - Notes
    - Statistical manipulation of the data is not, in and of itself, research!!
    - Research goes one step further and demands interpretation of the data
      - In finding median, mean, or standard deviation, we have not interpreted the data, nor have we extracted any meaning from them
        - » We only described the center and spread of the data
        - » We have attempted only to see what the data look like
        - » We should look for conditions that are forcing the data to behave as they do

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of association: Correlation
    - Correlation
      - The statistical process by which we discover whether two or more variables are in some way associated with one another
      - The resulting statistics is called correlation coefficient
    - Correlation coefficient
      - is a number between -1 and +1
      - Most correlation coefficients are decimals (either positive or negative)

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of association: Correlation…
    - Correlation coefficient …
      - Tells us two different things about the relationship between two variables
        - » Direction
          - The direction of the relationship is indicated by the sign of the correlation coefficient
          - If positive, as one variable increases, the other variable also increases
          - A negative number indicates an inverse relationship, or negative correlation: As one variable increases, the other variable decreases
        - » Strength
          - Indicated by the size of the correlation coefficient
          - Correlation of +1 or -1 indicates a perfect correlation
          - A number close to +1 or -1 indicates a strong correlation
          - A number close to 0 indicates weak correlation
          - Any number in between (e.g., 0.40s and 0.50s) indicates a moderate correlation

Strategies for analyzing quantitative data…

- Descriptive statistics… : Correlation coefficient …

Statistic	*Symbol*	*Data for Which It's Appropriate*
		Parametric Statistics
Pearson product moment correlation	r	Both variables involve continuous data.
Coefficient of determination	R^2	This is the square of the Pearson product moment correlation; thus, both variables involve continuous data.
Point biserial correlation	r_{pb}	One variable is continuous; the other involves discrete, dichotomous, and perhaps nominal data (e.g., Democrats vs. Republicans, males vs. females).
Biserial correlation	r_b	Both variables are continuous, but one has been artificially divided into an either-or dichotomy (e.g., "above freezing" vs. "below freezing," "pass" vs. "fail").
Phi coefficient	ϕ	Both variables are true dichotomies.
Triserial correlation	r_{tri}	One variable is continuous; the other is a trichotomy (e.g., "low," "medium," "high").
Partial correlation	$r_{12 \cdot 3}$	The relationship between two variables exists, in part, because of their relationships with a third variable, and the researcher wants to "factor out" the effects of this third variable (e.g., what is the relationship between motivation and student achievement when IQ is held constant statistically?).
Multiple correlation	$R_{1 \cdot 23}$	One variable is related to two or more variables; here the researcher wants to compute the first variable's *combined* relationship with the others.

Strategies for analyzing quantitative data…

- Descriptive statistics… : Correlation coefficient …

Statistic	Symbol	Data for Which It's Appropriate
		Nonparametric Statistics
Spearman rank order correlation (Spearman's rho)	ρ	Both variables involve rank-ordered data and so are ordinal in nature.
Kendall coefficient of concordance	*W*	Both variables involve rankings (e.g., rankings made by independent judges regarding a particular characteristic) and hence are ordinal data, and the researcher wants to determine the degree to which the rankings are similar.
Contingency coefficient	*C*	Both variables involve nominal data.
Kendall's tau correlation	τ	Both variables involve ordinal data; the statistic is especially useful for small sample sizes (e.g., $N < 10$).

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of association: Correlation…
    - Correlation coefficient …
      - Most widely used statistics is the Pearson product moment correlation (Pearson r) and Spearman rank order correlation (Spearman's rho)
      - All correlation statistics presented previously are based on the assumption that the relationship between the two variables is linear
        - » As one variable continues to increase, the other continues to increase (for a positive correlation) or decrease (for a negative correlation)
      - U-shaped and other nonlinear relationships can be detected through scatter plots and other graphic techniques, as well as through certain kinds of statistical analyses

Strategies for analyzing quantitative data…

- Descriptive statistics…
  - Measures of association: Correlation…
    - Note
      - Statistical correlation between two characteristics depends, in part, on how well those characteristics have been measured
      - Correlation does not necessarily indicate causation

Strategies for analyzing quantitative data…

- Inferential statistics
  - Allow us to draw inferences about large populations from relatively small samples
  - Has two main functions
    - To estimate a population parameter from a random sample
    - To test statistically based hypotheses

Strategies for analyzing quantitative data…

- Inferential statistics…
  - Estimating population parameters
    - While conducting a research, we use a sample to learn about the larger population from which the sample has been drawn
    - Example
      - Estimate population parameters related to central tendency (the mean, or μ) with sample mean X or M
    - Statistical estimates of population parameters are based on the assumption that the sample is randomly chosen and representative of the total population
    - Random samples from populations display roughly the same characteristics as the populations from which they were selected

Strategies for analyzing quantitative data…

- Inferential statistics…
  - Estimating population parameters…
    - Different samples-even when each has been randomly selected from the same population-will almost certainly yield slightly different estimates of the overall population
      - This difference between the population parameter and the sample statistics constitutes an error in our estimation
        - » How big the error is not known as the population parameter is not known
    - Known points (e.g., for mean)
      - The mean we might obtain from an infinite number of random samples form a normal distribution
      - The mean of this distribution of sample means is equal to the mean of the population from which the samples have been drawn(μ)
      - The standard deviation of this distribution of sample means is directly related to the standard deviation of the characteristic in question for the overall population
    - Larger samples yield more accurate estimates of population parameters

Strategies for analyzing quantitative data…

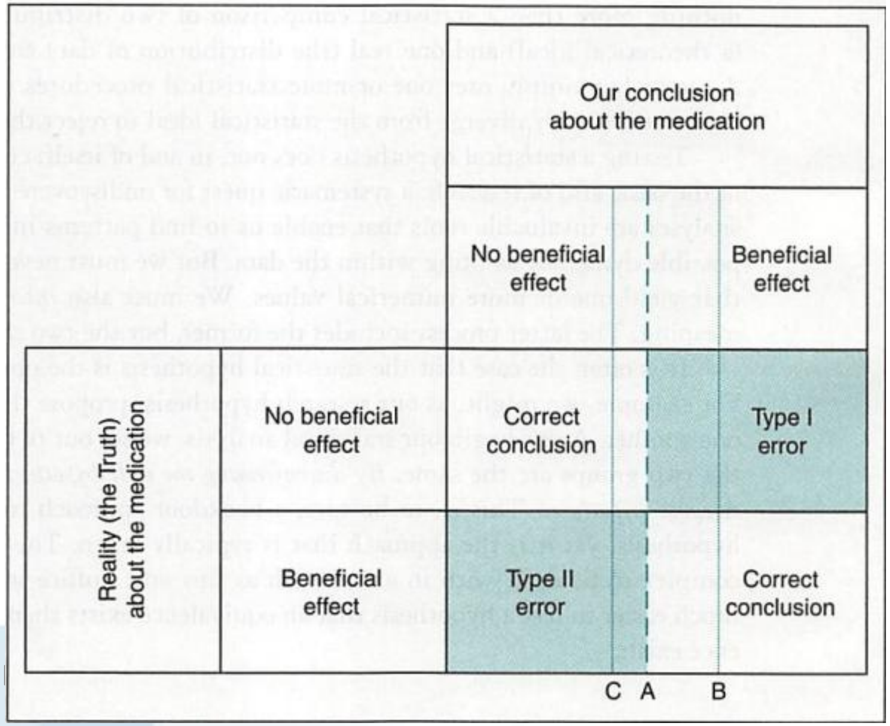
- Inferential statistics…
  - Testing hypothesis
    - Hypothesis can be defined differently, in different contexts
      - Research hypothesis
        - » A researcher speculates about how the research problem or one of its sub-problems might be resolved
        - » is a reasonable conjecture, an educated guess, a theoretically or empirically based prediction
        - » Purpose
          - Provides a temporary objective, an operational target, a logical framework that guides a researcher as he or she collects and analyzes data
      - Statistical hypothesis
        - » Refers to the null hypothesis (H_0)
          - Postulates that any result observed is the result of chance alone
        - » This process of comparing observed data with the results that we would expect from chance alone is called testing the null hypothesis

Strategies for analyzing quantitative data…

- Inferential statistics…
  - Testing hypothesis…
    - Statistical hypothesis…
      - » At what point do researchers decide that a result has not occurred by chance alone?
        - One common cutoff is a 1-in-20 probability, i.e., a result that would occur, on average, only one time in every 20 times (5%) probably is not due to chance but instead to another, systematic factor that is influencing the data
        - More rigorous cut off is a 1-in-100
      - » The probability that researchers use as their cutoff point, whether .05, .01, or some other figure, is the significance level, or alpha (α)
      - » A result that, based on this criterion, we deem not to be due to chance is called a statistically significant result
        - In this case the null hypothesis is rejected
        - We take the alternative hypothesis – the research hypothesis – as being more probable

Strategies for analyzing quantitative data…

- Inferential statistics…
  - Testing hypothesis…
    - Errors in hypothesis testing
      - Statistical hypothesis testing is all a matter of probabilities, and there is always the chance that we could make either a Type I or Type II error
      - Example: Medication vs placebo



Strategies for analyzing quantitative data…

- Inferential statistics…
  - Testing hypothesis…
    - Errors in hypothesis testing…
      - We can decrease the odds of making a Type I error by lowering our level of significance, say, from .05 to .01
        - » However, this increases the likelihood that we will make a Type II, i.e., we will fail to reject a null hypothesis that is incorrect
        - » We can decrease the odds of making a Type II error by increasing our level of significance

        $\Rightarrow$ Trade-of: Whenever you decrease the risk of making one, you increase the risk of making the other

Strategies for analyzing quantitative data…

- Inferential statistics…
  - Testing hypothesis…
    - Errors in hypothesis testing…
      - To increase the power of statistical testing
        - » Use as large a sample size as is reasonably possible
        - » Maximize the validity and reliability of your measures
        - » Use parametric rather than non parametric statistics whenever possible

Strategies for analyzing quantitative

- Inferential statistics…
  - Testing hypothesis…
  - Examples of statistical testing

Statistical Procedure	Purpose
	Parametric Statistics
Student's *t*-test	To determine whether a statistically significant difference exists between two means. A *t*-test takes slightly different forms depending on whether the two means come from separate, independent groups (an *independent-samples t*-test) or, instead, from a single group or two interrelated groups (a *dependent-samples t*-test).
Analysis of variance (ANOVA)	To examine differences among three or more means by comparing the variances (s^2) both within and across groups. As is true for *t*-tests, ANOVAs take slightly different forms for separate, independent groups and for a single group; in the latter case, a *repeated-measures* ANOVA is called for. If an ANOVA yields a significant result (i.e., a significant value for *F*), you should follow up by comparing various pairs of means using a *post hoc comparison of means*.
Analysis of covariance (ANCOVA)	To look for differences among means while controlling for the effects of a variable that is correlated with the dependent variable (the former variable is called a *covariate*). This technique can be statistically more powerful than ANOVA (i.e., it decreases the probability of a Type II error).
t-test for a correlation coefficient	To determine whether a Pearson product moment correlation coefficient (*r*) is larger than would be expected from chance alone.
Regression	To examine how effectively one or more variables allow(s) you to predict the value of another (dependent) variable. A *simple linear regression* generates an equation in which a single independent variable yields a prediction for the dependent variable. A *multiple linear regression* yields an equation in which two or more independent variables are used to predict the dependent variable.
Factor analysis	To examine the correlations among a number of variables and identify clusters of highly interrelated variables that reflect underlying themes, or *factors*, within the data.

Strat

- Inferential statistics…
  - Testing hypothesis…
  - Examples of statistical testing

Statistical Procedure	Purpose
Structural equation modeling (SEM)	To examine the correlations among a number of variables—often with different variables measured for a single group of people at different points in time—in order to identify possible causal relationships (*paths*) among the variables. SEM encompasses such techniques as *path analysis* and *confirmatory analysis* and is typically used to test a previously hypothesized model of how variables are causally interrelated. SEM enables a researcher to identify a *mediator* in a relationship: a third variable that may help explain why Variable A seemingly leads to Variable B (i.e., Variable A affects the mediating variable, which in turn affects Variable B). SEM also enables a researcher to identify a *moderator* of a relationship: a third variable that alters the nature of the relationship between Variables A and B (e.g., Variables A and B might be correlated when the moderating variable is high but not when it is low, or vice versa). (Mediating and moderating variables are discussed in more detail in Chapter 2.) When using SEM, the researcher must keep in mind that the data are *correlational* in nature; thus, any conclusions about cause-and-effect relationships are speculative at best.
Nonparametric Statistics	
Mann-Whitney *U*	To compare the medians of two groups when the data are ordinal rather than interval in nature. This procedure is the nonparametric counterpart of the independent-samples *t*-test in parametric statistics.
Kruskal-Wallis test	To compare three or more group medians when the data are ordinal rather than interval in nature. This procedure is the nonparametric counterpart of ANOVA.
Wilcoxon signed-rank test	To compare the medians of two correlated variables when the data are ordinal rather than interval in nature. This procedure is a nonparametric equivalent of a dependent-samples *t*-test in parametric statistics.
Chi-square (χ^2) goodness-of-fit test	To determine how closely observed frequencies or probabilities match expected frequencies or probabilities. A chi-square can be computed for nominal, ordinal, interval, or ratio data.
Odds ratio	To determine whether two dichotomous nominal variables (e.g., smokers vs. nonsmokers and presence vs. absence of heart disease) are significantly correlated. This is one nonparametric alternative to a *t*-test for Pearson's *r*.
Fisher's exact test	To determine whether two dichotomous variables (nominal or ordinal) are significantly correlated when the sample sizes are quite small (e.g., $n < 30$). This is another nonparametric alternative to a *t*-test for Pearson's *r*.

Threats to validity

- Reading assignment