Introduction to quantitative analysis

GSTTP research mini-course

Corrina Moucheraud, UCLA FSPH

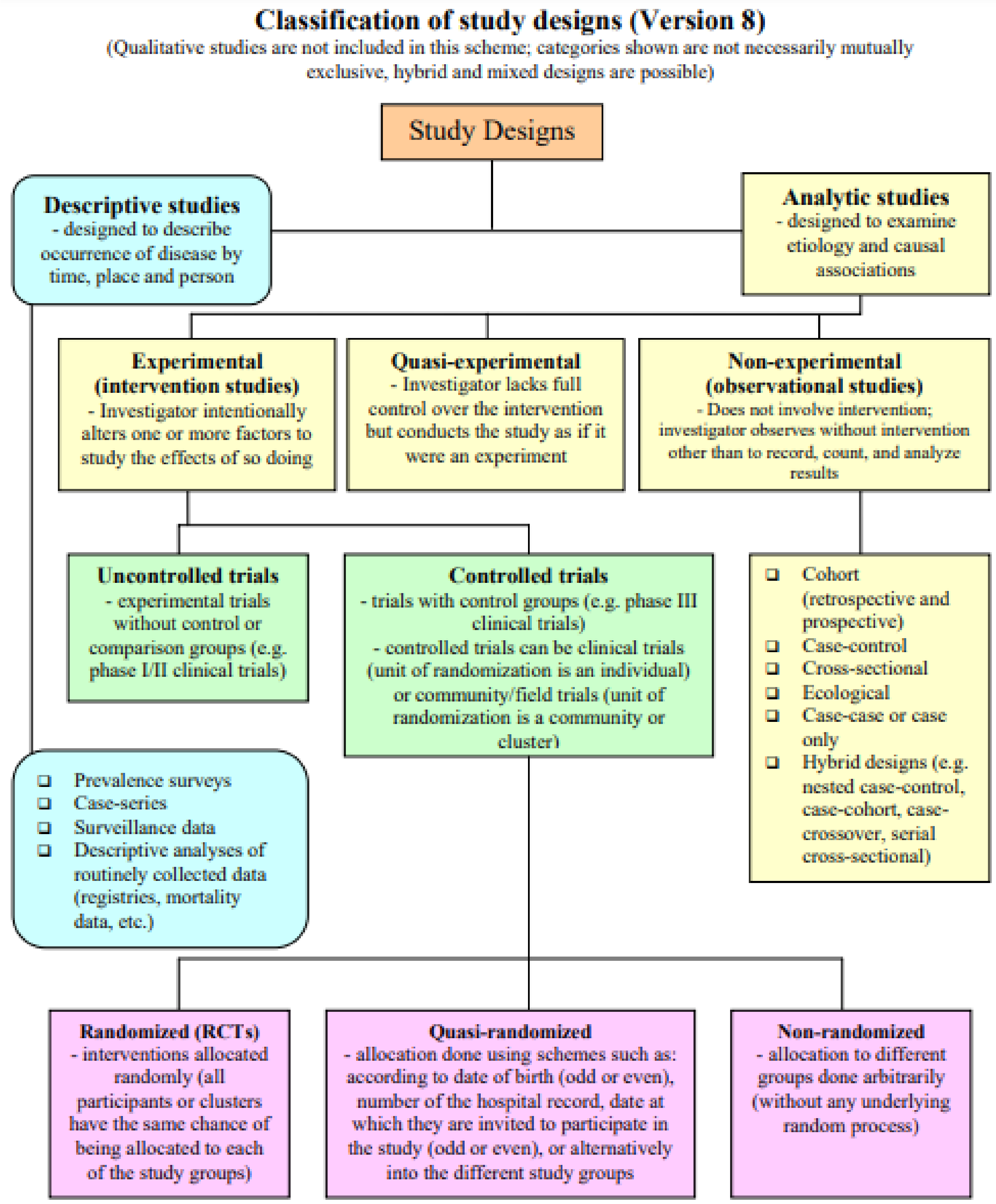
26 April 2021

Learning objectives

- Assess how study design and quantitative data (format, approach) shape quantitative analysis: research questions and hypotheses, choice of analysis methods, formulation and interpretation of results.
- *Describe best practices of quantitative data visualization (charts and tables) and critique examples.* → *We are going to do this later instead*

Typology of study designs

- What type of study are you undertaking?



Classification of study designs (Version 8)

(Qualitative studies are not included in this scheme; categories shown are not necessarily mutually exclusive, hybrid and mixed designs are possible)

Study Designs

Descriptive studies
- designed to describe occurrence of disease by time, place and person

Analytic studies
- designed to examine etiology and causal associations

Experimental (intervention studies)
- Investigator intentionally alters one or more factors to study the effects of so doing

Quasi-experimental
- Investigator lacks full control over the intervention but conducts the study as if it were an experiment

Non-experimental (observational studies)
- Does not involve intervention; investigator observes without intervention other than to record, count, and analyze results

Uncontrolled trials
- experimental trials without control or comparison groups (e.g. phase I/II clinical trials)

Controlled trials
- trials with control groups (e.g. phase III clinical trials)
- controlled trials can be clinical trials (unit of randomization is an individual) or community/field trials (unit of randomization is a community or cluster)

❑ Cohort (retrospective and prospective)
❑ Case-control
❑ Cross-sectional
❑ Ecological
❑ Case-case or case only
❑ Hybrid designs (e.g. nested case-control, case-cohort, case-crossover, serial cross-sectional)

❑ Prevalence surveys
❑ Case-series
❑ Surveillance data
❑ Descriptive analyses of routinely collected data (registries, mortality data, etc.)

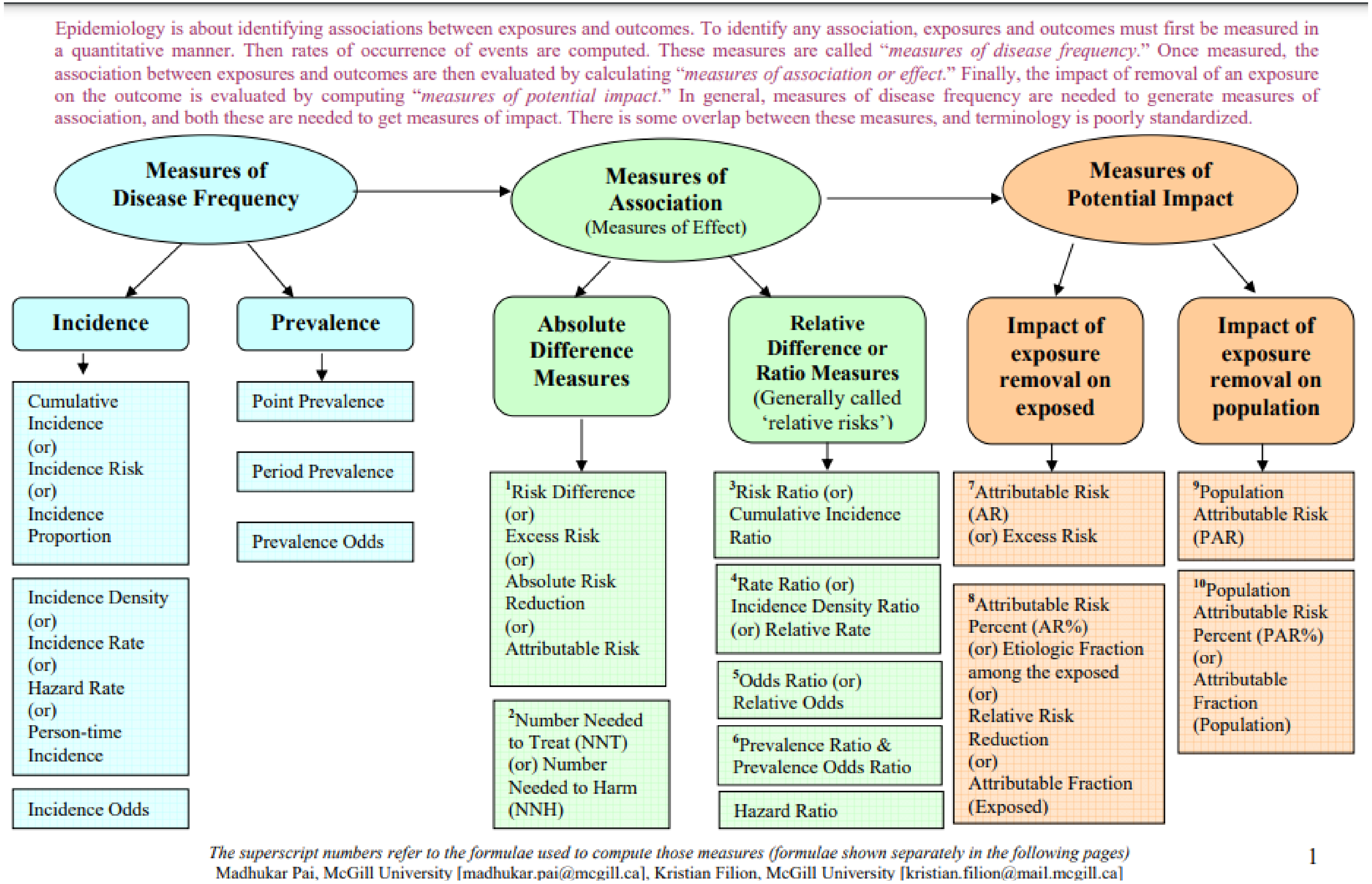
Randomized (RCTs)
- interventions allocated randomly (all participants or clusters have the same chance of being allocated to each of the study groups)

Quasi-randomized
- allocation done using schemes such as: according to date of birth (odd or even), number of the hospital record, date at which they are invited to participate in the study (odd or even), or alternatively into the different study groups

Non-randomized
- allocation to different groups done arbitrarily (without any underlying random process)

www.teachepi.org/

Quick side note: Studies in epidemiology



Epidemiology is about identifying associations between exposures and outcomes. To identify any association, exposures and outcomes must first be measured in a quantitative manner. Then rates of occurrence of events are computed. These measures are called "*measures of disease frequency*." Once measured, the association between exposures and outcomes are then evaluated by calculating "*measures of association or effect*." Finally, the impact of removal of an exposure on the outcome is evaluated by computing "*measures of potential impact*." In general, measures of disease frequency are needed to generate measures of association, and both these are needed to get measures of impact. There is some overlap between these measures, and terminology is poorly standardized.

Measures of Disease Frequency

- **Incidence**
  - Cumulative Incidence (or) Incidence Risk (or) Incidence Proportion
  - Incidence Density (or) Incidence Rate (or) Hazard Rate (or) Person-time Incidence
  - Incidence Odds
- **Prevalence**
  - Point Prevalence
  - Period Prevalence
  - Prevalence Odds

Measures of Association (Measures of Effect)

- **Absolute Difference Measures**
  - [1]Risk Difference (or) Excess Risk (or) Absolute Risk Reduction (or) Attributable Risk
  - [2]Number Needed to Treat (NNT) (or) Number Needed to Harm (NNH)
- **Relative Difference or Ratio Measures** (Generally called 'relative risks')
  - [3]Risk Ratio (or) Cumulative Incidence Ratio
  - [4]Rate Ratio (or) Incidence Density Ratio (or) Relative Rate
  - [5]Odds Ratio (or) Relative Odds
  - [6]Prevalence Ratio & Prevalence Odds Ratio
  - Hazard Ratio

Measures of Potential Impact

- **Impact of exposure removal on exposed**
  - [7]Attributable Risk (AR) (or) Excess Risk
  - [8]Attributable Risk Percent (AR%) (or) Etiologic Fraction among the exposed (or) Relative Risk Reduction (or) Attributable Fraction (Exposed)
- **Impact of exposure removal on population**
  - [9]Population Attributable Risk (PAR)
  - [10]Population Attributable Risk Percent (PAR%) (or) Attributable Fraction (Population)

The superscript numbers refer to the formulae used to compute those measures (formulae shown separately in the following pages)

Madhukar Pai, McGill University [madhukar.pai@mcgill.ca], Kristian Filion, McGill University [kristian.filion@mail.mcgill.ca]

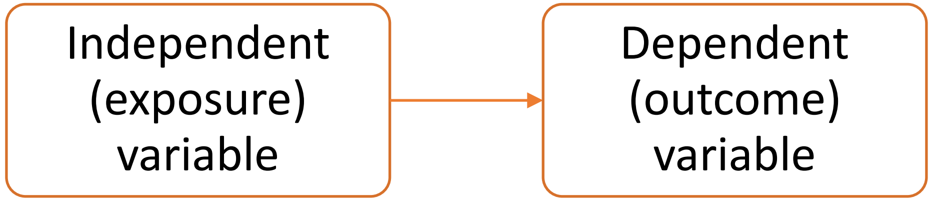
www.teachepi.org/

Critically important that you have a clear research question up-front

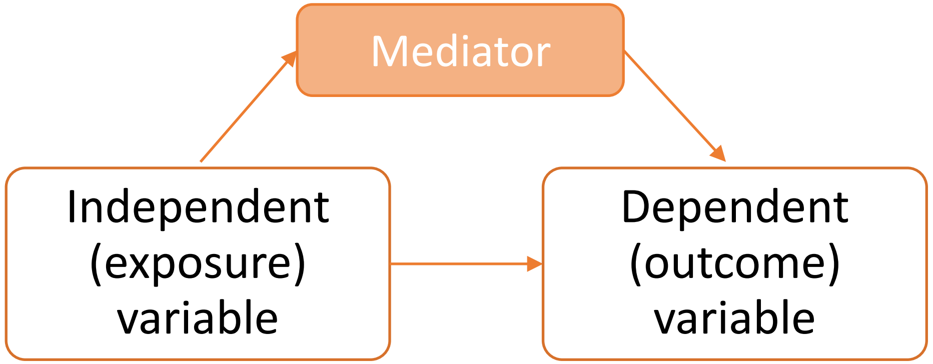
- Let’s say that I surveyed each of you after every one of these lectures
- What research questions could I answer?

- From your research question, everything else flows.
  - Is it a “how much” question? Or a “who” question? Or a “why” question? Or…
  - This dictates your study design and how you will analyze & present your results
- Also, need to be clear about what outcome you’re measuring

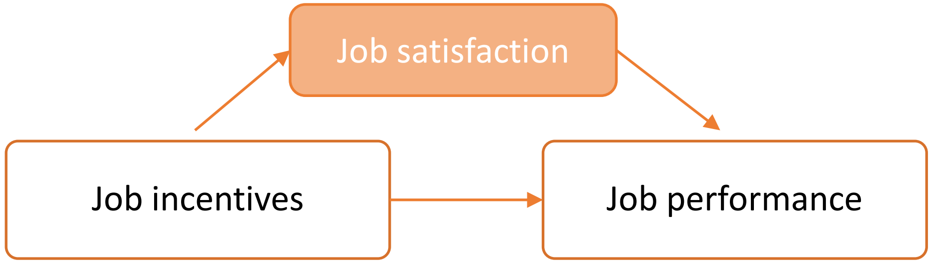
Relationships between variables

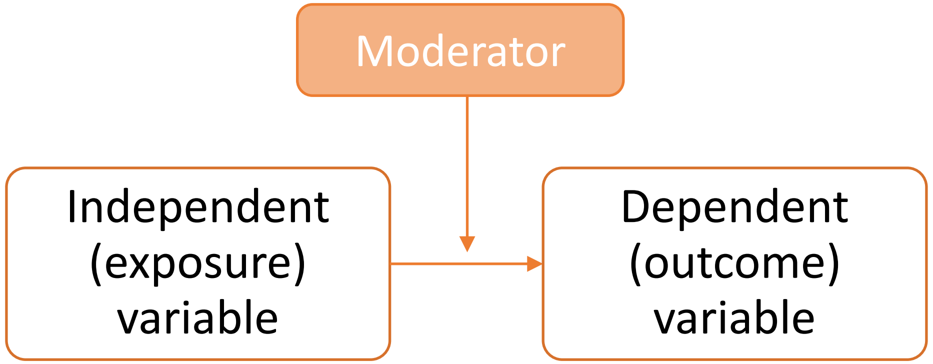


- Ideal scenario! Very clear & easy to interpret. But, very rare.
- This is what randomized control trials emulate
- Asbestos exposure → Risk of mesothelioma

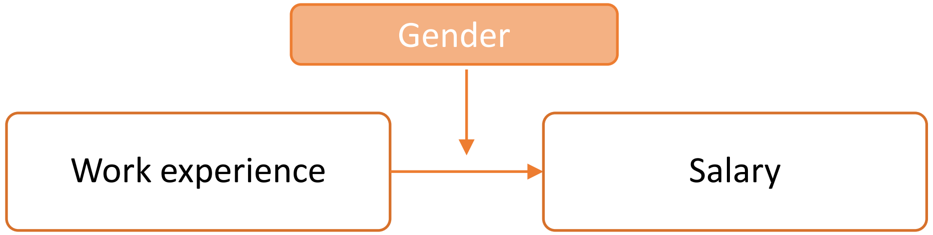


- Mediators are alternative pathways between IV & DV
  - Direct effect + indirect effect (operates through mediator) = total effect of IV on DV



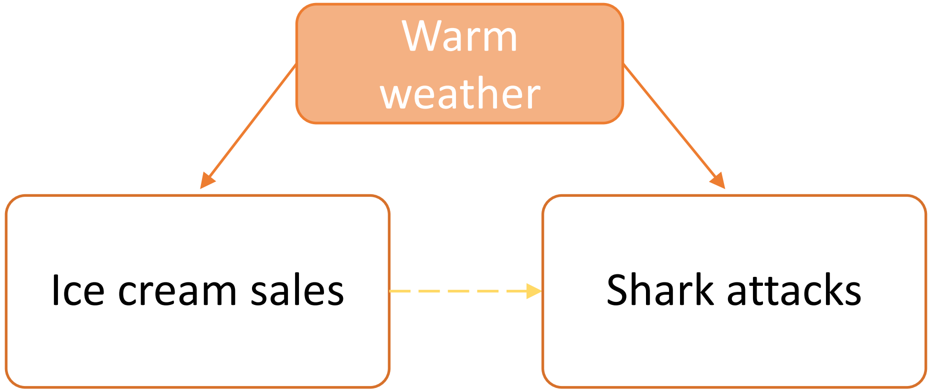


- Moderators impact the relationship between IV & DV
  - Aka, effect modifiers: the relationship is not the same for everybody



Quick note on confounding

- “Confounding” is a term you will probably hear <u>all the time</u>
- Affects ability to draw causal inferences from observed relationships
- Because it affects both the IV & DV, creates a spurious association between these if it is left unmeasured



Your job as a researcher

- Be specific, thoughtful, and clear up-front about your research question(s), your study design, what you are measuring as what type of variable (independent, dependent, mediator, moderator, etc.)

- Theoretical frameworks and existing conceptual models can help you specify these
- Also, discussion with your collaborators and experts in the field

Research questions

- Should end in a question mark!

- “Understand the patient population at Hospital ABC”
  - Better: “Who is coming to Hospital ABC”
    - Better x2: “What is the age distribution of people with scheduled outpatient appts at Hospital ABC during January 2020”
      - Note that this is a different question than “What is the ***average age*** of people …” or “What is the age distribution of people who ***attended outpatient appts*** at Hospital ABC during January 2020”

Improved research questions, ex. 2

- “How diverse is the patient population at Hospital ABC”
    - Better: “How many Latino patients come to Hospital ABC”
        - Better x2: “What percentage of adults attending outpatient appts at Hospital ABC during Jan 2020 identify as Latino?”
            - Different than: “What is the ***number*** of adults attending outpatient appts at Hospital ABC during Jan 2020 who identify as Latino”
    - What information does this tell us?

What doesn’t this tell us?

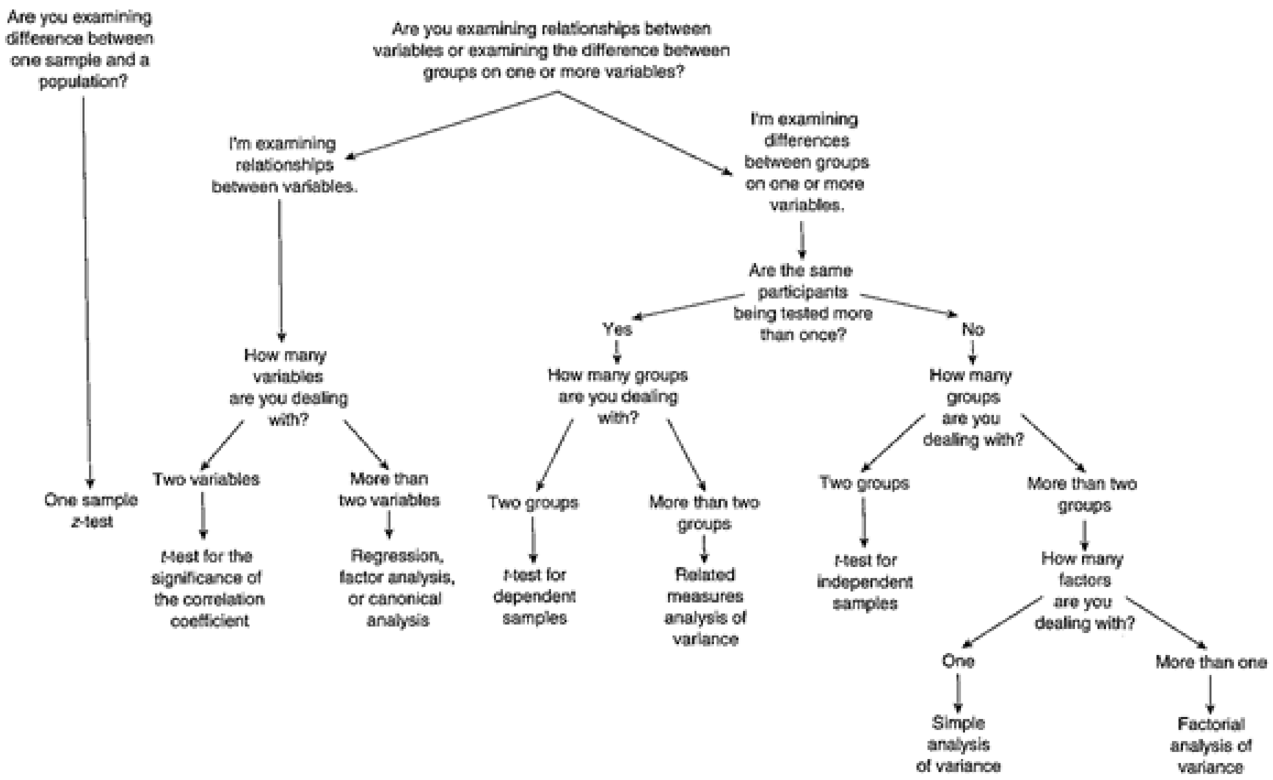
- How many Spanish-speaking staff do we need?
    - ➢Need to know patient language preferences
- How many additional Spanish-speaking staff do we need? (… what types, which service lines)
    - ➢Need to know current staff’s language proficiency
- What care-seeking barriers do Latino patients face?
    - ➢Need additional info about care-seeking patterns + also qualitative data may be informative

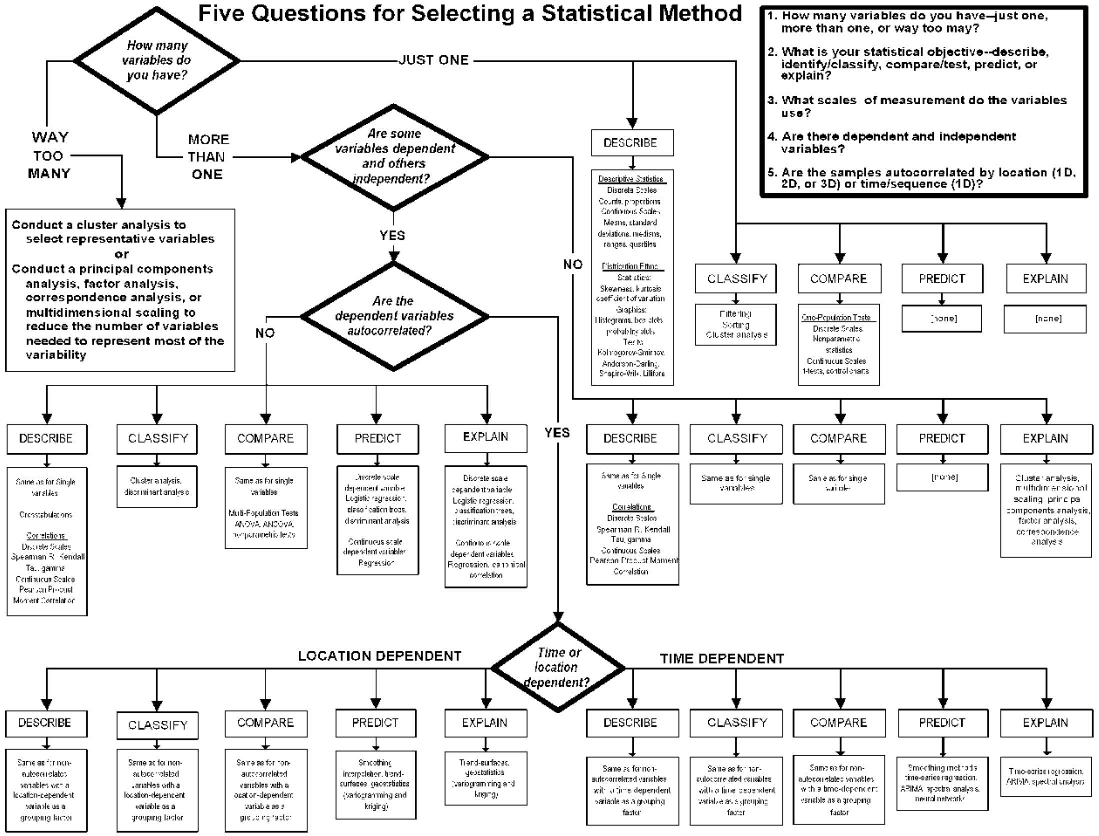
Ok, so you set things up well & collected your data. Now what?

- Remember data types:
  - Dichotomous
  - Nominal with >2 categories
  - Ordinal
  - Continuous

- Depending on type of data, can undertake different types of analyses

Lots of nice “flow charts” out there to help guide you


Are you examining difference between one sample and a population?
One sample z-test
Are you examining relationships between variables or examining the difference between groups on one or more variables?
I'm examining relationships between variables.
How many variables are you dealing with?
Two variables
t-test for the significance of the correlation coefficient
More than two variables
Regression, factor analysis, or canonical analysis
I'm examining differences between groups on one or more variables.
Are the same participants being tested more than once?
Yes
How many groups are you dealing with?
Two groups
t-test for dependent samples
More than two groups
Related measures analysis of variance
No
How many groups are you dealing with?
Two groups
t-test for independent samples
More than two groups
How many factors are you dealing with?
One
Simple analysis of variance
More than one
Factorial analysis of variance


Five Questions for Selecting a Statistical Method

1. How many variables do you have—just one, more than one, or way too may?
2. What is your statistical objective--describe, identify/classify, compare/test, predict, or explain?
3. What scales of measurement do the variables use?
4. Are there dependent and independent variables?
5. Are the samples autocorrelated by location (1D, 2D, or 3D) or time/sequence (1D)?

How many variables do you have?
JUST ONE
DESCRIBE
Descriptive Statistics
Discrete Scales
Counts, proportions
Continuous Scales
Means, standard deviations, medians, ranges, quartiles
Distribution Fitting
Statistics:
Skewness, kurtosis coefficient of variation
Graphics:
Histograms, box plots probability plots
Tests
Kolmogorov-Smirnov, Anderson-Darling, Shapiro-Wilk, Lilliford
CLASSIFY
Filtering
Sorting
Cluster analysis
COMPARE
One-Population Tests
Discrete Scales
Nonparametric statistics
Continuous Scales
t-tests, control charts
PREDICT
[none]
EXPLAIN
[none]
WAY TOO MANY
Conduct a cluster analysis to select representative variables
or
Conduct a principal components analysis, factor analysis, correspondence analysis, or multidimensional scaling to reduce the number of variables needed to represent most of the variability
MORE THAN ONE
Are some variables dependent and others independent?
NO
DESCRIBE
Same as for Single variables
Correlations
Discrete Scales
Spearman R, Kendall Tau, gamma
Continuous Scales
Pearson Product Moment Correlation
CLASSIFY
Same as for single variables
COMPARE
Same as for single variable
PREDICT
[none]
EXPLAIN
Cluster analysis, multidimensional scaling, principal components analysis, factor analysis, correspondence analysis
YES
Are the dependent variables autocorrelated?
NO
DESCRIBE
Same as for Single variables
Crosstabulations
Correlations
Discrete Scales
Spearman R, Kendall Tau, gamma
Continuous Scales
Pearson Product Moment Correlation
CLASSIFY
Cluster analysis, discriminant analysis
COMPARE
Same as for single variables
Multi-Population Tests
ANOVA, ANCOVA, nonparametric tests
PREDICT
Discrete scale dependent variable
Logistic regression, classification trees, discriminant analysis
Continuous scale dependent variables
Regression
EXPLAIN
Discrete scale dependent variable
Logistic regression, classification trees, discriminant analysis
Continuous scale dependent variables
Regression, canonical correlation
YES
Time or location dependent?
LOCATION DEPENDENT
DESCRIBE
Same as for non-autocorrelated variables with a location-dependent variable as a grouping factor
CLASSIFY
Same as for non-autocorrelated variables with a location-dependent variable as a grouping factor
COMPARE
Same as for non-autocorrelated variables with a location-dependent variable as a grouping factor
PREDICT
Smoothing, interpolation, trend-surfaces, geostatistics (variogramming and kriging)
EXPLAIN
Trend-surfaces, geostatistics (variogramming and kriging)
TIME DEPENDENT
DESCRIBE
Same as for non-autocorrelated variables with a time-dependent variable as a grouping factor
CLASSIFY
Same as for non-autocorrelated variables with a time-dependent variable as a grouping factor
COMPARE
Same as for non-autocorrelated variables with a time-dependent variable as a grouping factor
PREDICT
Smoothing methods, time-series regression, ARIMA, spectral analysis, neural networks
EXPLAIN
Time-series regression, ARIMA, spectral analysis

Types of analyses

- Descriptive
- Comparative

Solely about the sample we have observed

- Inferential

Using data from your sample to infer about population

Any time you see a p-value or confidence interval, it's from an inferential analysis

Description vs. inference

- Descriptive statistics: using data to show or summarize (describe) characteristics of a sample

- Inferential statistics: using data from a sample to make predictions about (infer) characteristics of a population

- *Predictive methods: based on what we've already seen, what do we expect to see in the future? How might this change if we alter X, Y, Z?*

What can descriptive statistics do?

- Raw data are too numerous and can be hard to detect meaningful patterns

- Descriptive statistics enable interpretation – but cannot draw conclusions beyond the sample studied

What can inferential statistics do?

- Might be impossible to survey a full population (“census”)

- Robustness of inference depends on how well your sample represents the population
  - Inherent uncertainty (sampling error) + bias

Inferential statistics

- You are a sample of:
  - Medical students at UCLA
  - Graduate students at UCLA
  - Students at UCLA
  - People who live in LA
  - Graduate students in the US
  - People who know about statistics
  - Humans
  - etc.

- To which of these group(s) would you be most comfortable inferring? i.e., for which population(s) are we a good sample?

→ “confidence” is a function of sampling

Hypothesis testing

- Null hypothesis (aka, H_0): there is no difference between population A & population B
  - By comparing sample_A to sample_B
  - p-value: probability that the null hypothesis is true

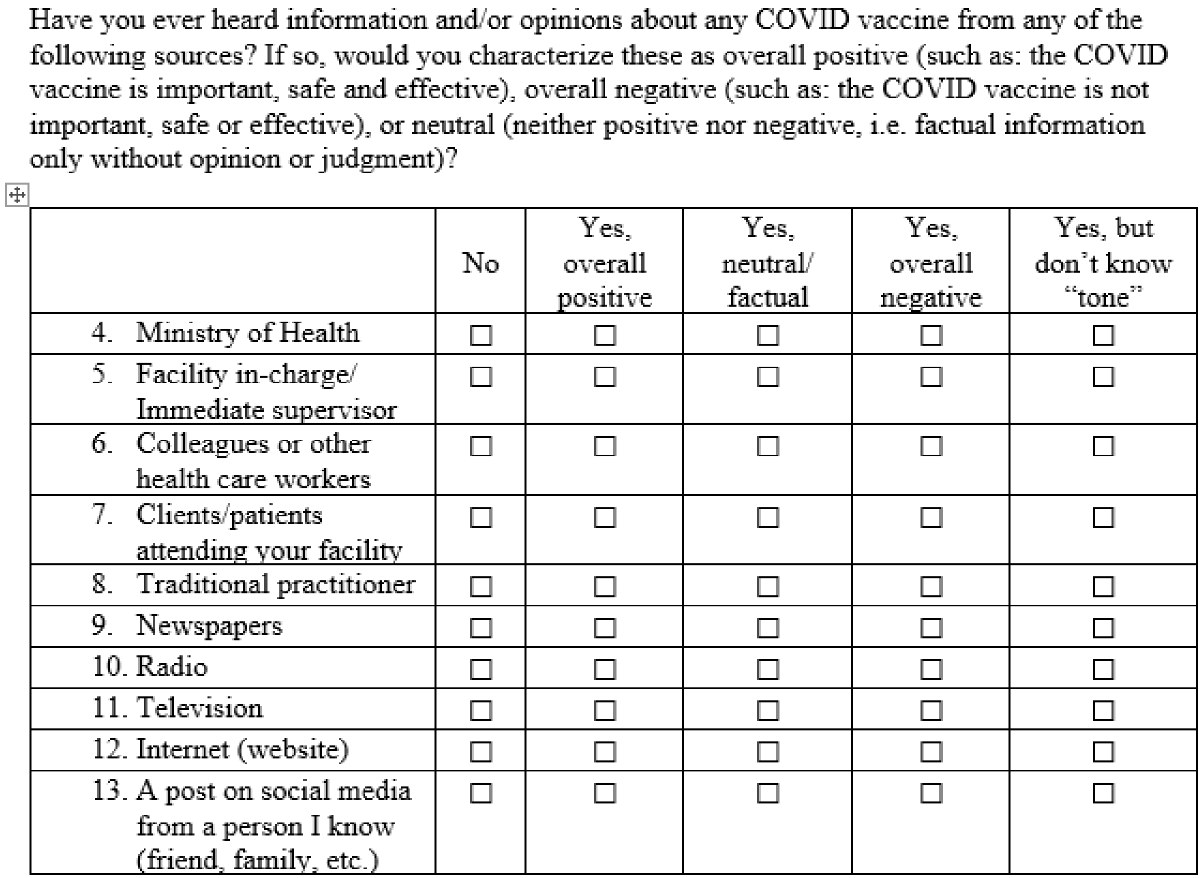
- Note: Continuous data exist in a distribution; the larger your sample size, the more stable/apparent the distribution of your data will be
  - We often assume normal distribution **BUT this can be an incorrect** assumption!! Be very careful about this.

Descriptive data with categorical variables

- Frequencies of occurrence: #s or %s
- Consider treating individually vs. combining… Depends on research q!

What are some ways we could analyze these data?

- What is most frequently positive source? Negative source?
- Overall do people hear positive or negative information?
- Are different sources, or types of sources more likely to be pos or neg?
- How many different sources of info do people hear?



Have you ever heard information and/or opinions about any COVID vaccine from any of the following sources? If so, would you characterize these as overall positive (such as: the COVID vaccine is important, safe and effective), overall negative (such as: the COVID vaccine is not important, safe or effective), or neutral (neither positive nor negative, i.e. factual information only without opinion or judgment)?

	No	Yes, overall positive	Yes, neutral/ factual	Yes, overall negative	Yes, but don't know "tone"
4. Ministry of Health	□	□	□	□	□
5. Facility in-charge/ Immediate supervisor	□	□	□	□	□
6. Colleagues or other health care workers	□	□	□	□	□
7. Clients/patients attending your facility	□	□	□	□	□
8. Traditional practitioner	□	□	□	□	□
9. Newspapers	□	□	□	□	□
10. Radio	□	□	□	□	□
11. Television	□	□	□	□	□
12. Internet (website)	□	□	□	□	□
13. A post on social media from a person I know (friend, family, etc.)	□	□	□	□	□

A note on analyzing continuous data

- If discrete and small range (e.g., number of pets that people have) can treat as categorical variable
  - If you took an average, would “2.25 cats” be meaningful?
  - So instead, think about each value as a response option of a categorical question: # and/or % of each
  - Sometimes we treat as continuous anyway (examples: total fertility rate [1.73 births per woman in the U.S.], average household size [2.53 people in the U.S.])

Descriptive statistics with continuous data

- If want to treat as continuous, decide: do I care about the middle or do I care about the spread?

- If the middle: median, mean, mode…

  **** Mean is sensitive to the distribution ****

- If the spread: range, variance/standard deviation, interquartile range…

- Often we care about both and may report both a middle-based statistic and a spread-based statistic, like the median and the SD

Inferential methods: a partial list

- t-tests: difference between 2 means (continuous variables)
- chi-square tests: difference between 2+ categorical variables
- ANOVA: difference between 3+ means
- Regression models (linear, logistic, etc.): predicted relationship between variables

A very simple (& admittedly not very good) example for us to walk through

- Research question: Are people who attend medical school taller than people who do not attend medical school?

  - H_0: Medical students are the same height as people not in medical school *(based on the sample of first-year DGSOM students who I've measured)*

    Usually we don't say this part "out loud"

  - H_A (aka H_1): Medical students are taller than people not in medical school *(based on my sample)*

    → NOTE: this is a one-sided hypothesis; I could have said "Medical students are a different height" and this would be two-sided (could be taller, could be shorter)

Descriptive statistics

- Could start with the mean & the median
  - Mean will be very sensitive (likely to get "pulled") if you have some really tall, or some really short, classmates

- But first-year DGSOM students are just a sample… So we need to make some inference if we want to address our research question

- The average height of first-year DGSOM students is 71 inches
- If I estimate that this has a 95% confidence interval of 68-74 inches, I am saying "*I am 95% sure that the true average height of the population [remember, think about what population you are a sample of!] lies between 68 and 74 inches*"

Inference & beware confounding!

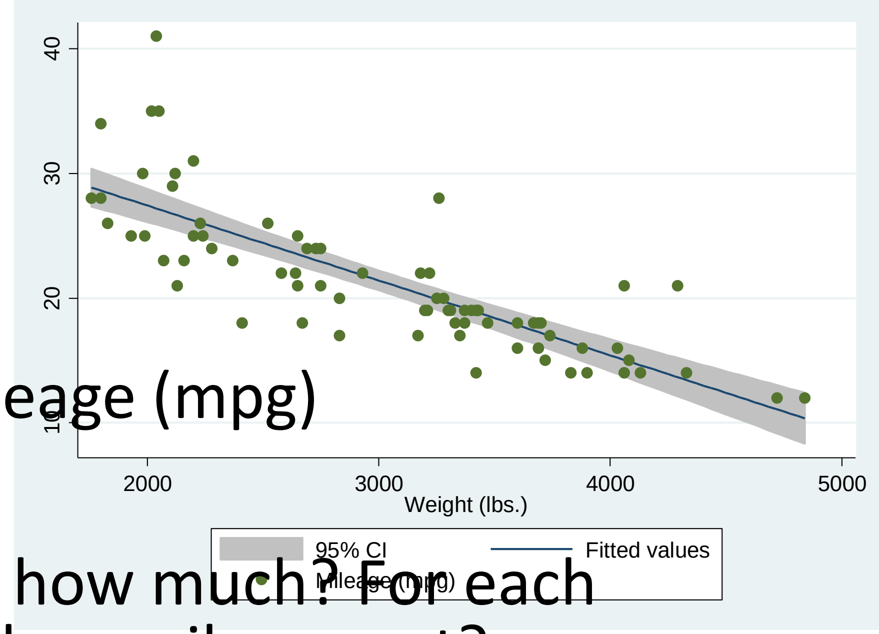
- To really answer my research question, I would need to compare the height of DGSOM students to the height of similar people who are not in medical school (want to avoid mediators, confounders, etc.)
  - Maybe really tall people were more likely to be recruited for varsity sports in high school & college, so less likely to take all the premed classes etc., so less likely to go to medical school → this is OK, it is a "common cause"
    - If we hypothesize this operates differently for boys & girls, however, we would need to include this as a moderator
  - Maybe the California sunshine was really helpful for kids' growth, and also DGSOM students are more likely to be from California → so our relationship between height & DGSOM status is confounded by growing up in California
- Let's assume you found a good comparison population

Inference & p-values & what it all means

- Could do a t-test of independent sample to compare the average height in sample$_A$ (DGSOM students) to average height in sample$_B$ (comparison group)
    - Will generate what is called a "test statistic" (a t-value in this case)
        - Compares our sample average value (71") to the average in the other sample
            - Null hypothesis says: the average height in sample$_B$ is also 71"
        - Big test statistic means big difference between the groups
    - AND, a p-value on this test statistic: what is the probability that this test statistic could be obtained if H_0 is true
        - We reject the null based on this probability
            - We never accept the null! We just reject, or fail to reject, it
- If our t-statistic has a p-value of 0.03 this can be read as:

There is a 3% (or less) chance that the observed difference in average height between sample$_A$ (DGSOM students) & sample$_B$ (comparison group) *and the true population difference* would have occurred if medical students are the same height as other people (if H_0 were true).

Regression models



- Two continuous variables – car weight, and mileage (mpg)
- We can see there is a negative association but, how much? For each additional pound of weight, how much worse does mileage get?
- This is a best-fit line: it minimizes the vertical distance from the line to each point
- You may recall that straight lines are expressed as: Y = mx+b
- Same for (linear) regression! At 0 lbs (intercept), mileage (Y) would be 39.4 mpg; each additional unit of X (pound of weight) subtracts 0.006 mpg
  - There is also an error term because the line is not fit perfectly: $Y=\alpha+\beta x+\varepsilon$
  - If there are multiple explanatory variables, equation expands: $Y=\alpha+\beta_1x_1+\beta_2x_2+\ldots+_+\varepsilon$

Resources

- Many (many many!) books, including:
  - Rosner, “Fundamentals of biostatistics”
  - Van Emden, “Statistics for terrified biologists”
  - Wheelan, “Naked statistics”
  - Coolidge, “Statistics: A gentle introduction”

- Stata has informative help files for programming all of this!
- Institute for Digital Research and Education at UCLA is amazing (https://idre.ucla.edu/)
  - Resources on their website (FAQ etc) + also consultations for UCLA community