TWO-DAY DYADIC DATA ANALYSIS WORKSHOP

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UCSF January 9th and 10th

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SMITH COLLEGE

A little about me...

Ucla BRUINS

UCLA SOCIAL SCIENCES DIVISION | DEPARTMENT OF Gender Studies

UCONN

Dyadic Data Analysis

Smith professor of:

- Psychology
- Statistical and Data Sciences

SMITH PIONEERS

What about you?

Workshop Materials

on GitHub

>Find the workshop schedule and data examples here:

https://randilgarcia.github.io/website/workshop/schedule.html

>Download ALL materials, including R-code, here:

https://github.com/RandiLGarcia/2day-dyad-workshop

DAY 1

- Definitions and Nonindependence
- Data Structures
- The Actor-Partner Interdependence Model (APIM)
- Generalized Mixed Modeling (i.e., for discrete outcomes)

Definitions: Distinguishability

- Can all dyad members be distinguished from one another based on a meaningful factor?
- Distinguishable dyads
  - Gender in heterosexual couples
  - Patient and caregiver
  - Race in mixed race dyads

All or Nothing

- If most dyad members can be distinguished by a variable (e.g., gender), but a few cannot, then can we say that the dyad members are distinguishable?
- No, we cannot!

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Indistinguishability

- There is no systematic or meaningful way to order the two scores

- Examples of indistinguishable dyads
  - Same-sex couples
  - Twins
  - Same-gender friends
  - Mix of same-sex and heterosexual couples
  - When all dyads are hetero except for <u>even one couple</u>!

It can be complicated…

- Distinguishability is a mix of theoretical and empirical considerations.

- For dyads to be considered distinguishable:
  1. It should be theoretically important to make such a distinction between members.
  2. Also it should be shown that empirically there are differences.

- Sometimes there can be two variables that can be used to distinguish dyad members: Spouse vs. patient; husband vs. wife.

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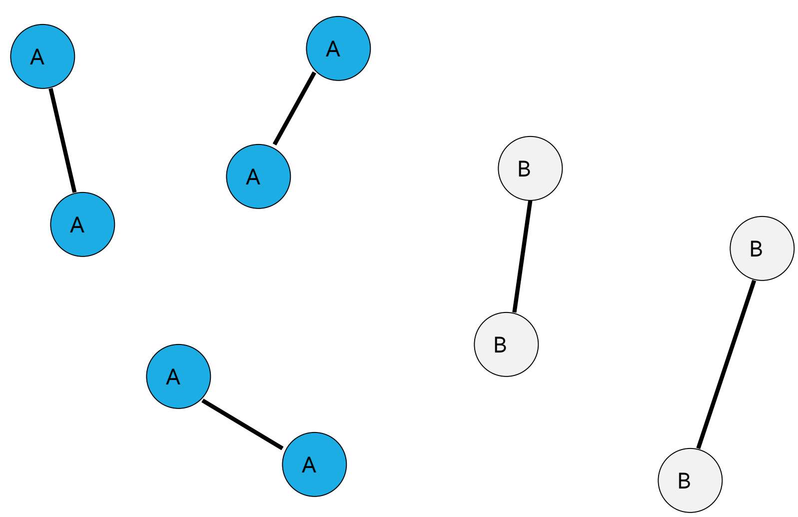
Types of Variables

- Between Dyads
  - Variable varies from dyad to dyad, BUT within each dyad all individuals have the same score
    - Example: Length of relationship

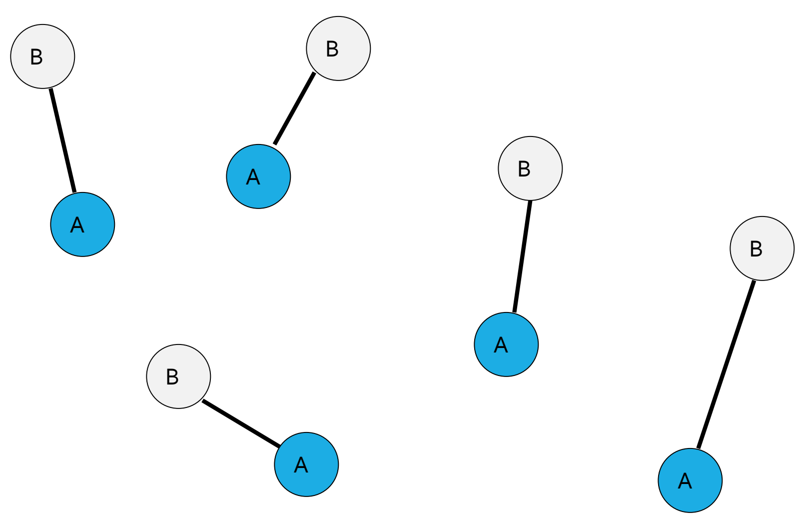
- Called a level 2, or macro variable in multilevel modeling



Between

Within Dyads

- Variable varies from person to person within a dyad, BUT there is no variation on the dyad average from dyad to dyad.
  - Percent time talking in a dyad
  - Reward allocation if each dyad is assigned the same total amount
- $X_1 + X_2$ equals the same value for each dyad
- Note: If in the data, there is a dichotomous within-dyads variable, then dyad members *can* be distinguished on that variable. But that doesn't mean it would be theoretically meaningful to do so.



Within

Mixed Variable

- Variable varies both between dyads and within dyads.
- In a given dyad, the two members may differ in their scores, and there is variation across dyads in the average score.
  - Age in married couples
  - Lots-o personality variables
- Most outcome variables are mixed variables.

It can be complicated…

Can you think of a variable that can be **between-dyads**, **within-dyads**, or **mixed** across different samples?

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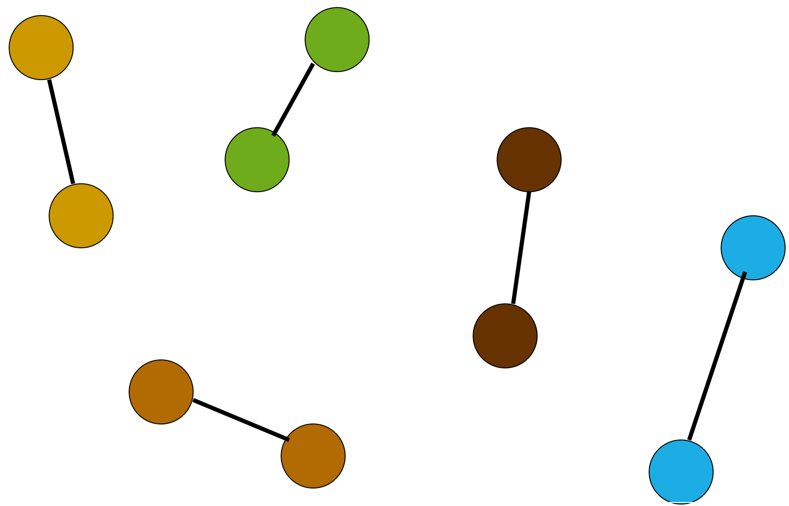
TYPES OF DYADIC DESIGNS

Standard Dyadic Design

- Each person has one and only one partner.
- About 75% of research with standard dyadic design
- Examples: Dating couples, married couples, friends



Standard Design-Indistinguishable

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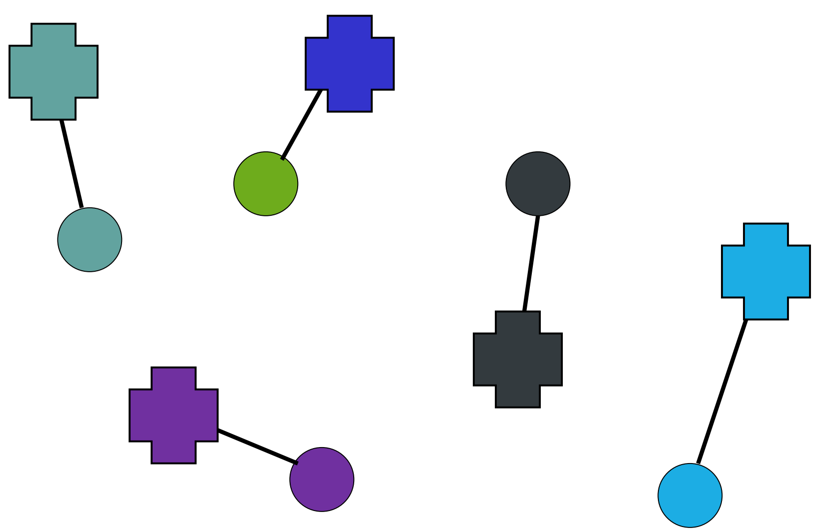

Standard Design - Distinguishable

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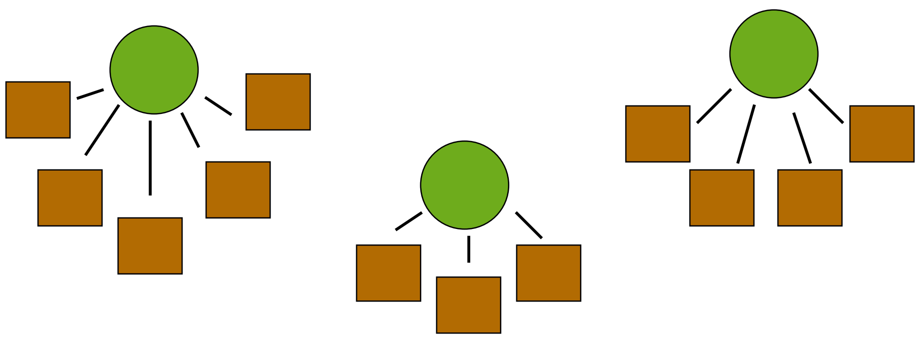
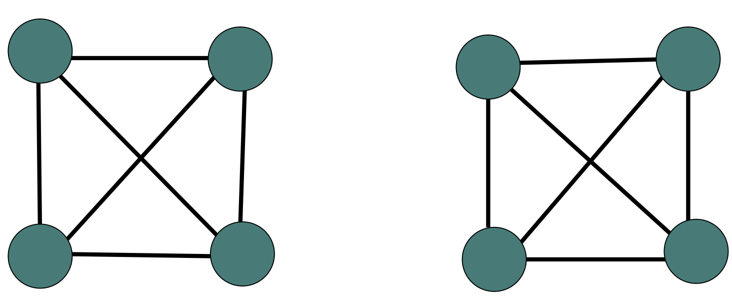
The One-with-Many Design

- All partners have the same role with the focal person
- For example, students with teachers or workers with managers



Round-Robin Design

- Social Relations Model (SRM)
- Examples: Team or family members rating one another



DATA STRUCTURES

Illustration of Data Structures: Individual

Dyad	*Person*	*X*	*Y*	*Z*
1	1	5	9	3
1	2	2	8	3
2	1	6	3	7
2	2	4	6	7
3	1	3	6	5
3	2	9	7	5

Illustration of Data Structures: Individual

AAAAA
AAAAA
AAAAA
AAAAA
BBBBB
BBBBB
BBBBB
BBBBB

Illustration of Data Structures: Dyad

Dyad	X_1	Y_1	Z_1	X_2	Y_2	Z_2[a]
1	5	9	3	2	8	3
2	6	3	7	4	6	7
3	3	6	5	9	7	5

Illustration of Data Structures: Dyad

AAAAABBBBB
AAAAABBBBB
AAAAABBBBB
AAAAABBBBB

Illustration of Data Structures: Pairwise

Dyad	*Person*	X_1	Y_1	Z_1	X_2	Y_2	Z_2[a]
1	1	5	9	3	2	8	3
1	2	2	8	3	5	9	3
2	1	6	3	7	4	6	7
2	2	4	6	7	6	3	7
3	1	3	6	5	9	7	5
3	2	9	7	5	3	6	5

[a]This variable is redundant with Z_1 and need not be included.

Illustration of Data Structures: Pairwise

AAAAABBBBB
AAAAABBBBB
AAAAABBBBB
AAAAABBBBB
BBBBBAAAAA
BBBBBAAAAA
BBBBBAAAAA
BBBBBAAAAA

R DEMO

Then break! Then more demo…

NONINDEPENDENCE IN DYADS

Negative Nonindependence

- Nonindependence is often defined as the proportion of variance explained by the dyad (or group).
- BUT, nonindependence can be negative…variance cannot!

- This is super important
- **<u>THE</u> MOST IMPORTANT THING ABOUT DYADS!**

How Might Negative Correlations Arise?

Examples

- **Division of labor:** Dyad members assign one member to do one task and the other member to do another. For instance, the amount of housework done in the household may be negatively correlated.

- **Power:** If one member is dominant, the other member is submissive. For example, self-objectification is negatively correlated in dyadic interactions.

Effect of Nonindependence

- Consequences of ignoring clustering classic MLM
  - Effect Estimates Unbiased
- For dyads especially
  - Standard Errors Biased
    - Sometimes too large
    - Sometimes too small
    - Sometimes hardly biased

Direction of Bias Depends on

1. Direction of Nonindependence
   - Positive
   - Negative
2. Is the predictor a between or within dyads variable? (or somewhere in between: mixed)

Effect of Ignoring Nonindependence on Significance Tests

	Positive	Negative
Between		
Within		

What Not To Do!

- Ignore it and treat individual as unit
- Discard the data from one dyad member and analyze only one members' data
- Collect data from only one dyad member to avoid the problem
- Treat the data as if they were from two samples (e.g., doing an analysis for husbands and a separate one for wives)
  - Presumes differences between genders (or whatever the distinguishing variable is)
  - Loss of power

What To Do

- Consider both individual and dyad in one analysis!
  1. Multilevel Modeling
  2. Structural Equation Modeling

Traditional Model: Random Intercepts

Micro level $$y_{ij} = b_{0j} + b_{1j}X_{1ij} + e_{ij}$$

Macro level $$b_{0j} = g_{00} + g_{01}Z_{1j} + u_{0j}$$

$$b_{1j} = g_{10}$$

- i from 1 to 2, because there are only 2 people in each "group".
- X_{1ij} is a mixed or within variable, and Z_{1j} is a between variable.
- Note b_{0j} is the common intercept for dyad j which captures the nonindependence.
- Works well with positive nonindependence, but not negative.

Alternative Model: Correlated Errors

Micro level

$$y_{1j} = b_0 + b_{1j}X_{11j} + e_{1j}$$

$$y_{2j} = b_0 + b_{1j}X_{12j} + e_{2j}$$

ρ called "*rho*"

Macro level $$b_{1j} = g_{10}$$

- ρ is the correlation between e_{1j} and e_{2j}, the 2 members' residuals (errors).
- Note b_0 is now the grand intercept
- Works well with positive nonindependence AND negative.

R DEMO

ACTOR-PARTNER INTERDEPENDENCE MODEL (APIM)

Actor-Partner Interdependence Model (APIM)

- A model that simultaneously estimates the effect of a person's own variable (actor effect) and the effect of same variable but from the partner (partner effect) on an outcome variable
- The actor and partner variables are the same variable from different persons.
- All individuals are treated as actors and partners.

Data Requirements

- Two variables, X and Y, and X causes or predicts Y
- Both X and Y are mixed variables—both members of the dyad have scores on X and Y.
- Example
  - Dyads, one a patient with a serious disease and other being the patient's spouse. We are interested in the effects of depression on relationship quality

Actor Effect

- Definition: The effect of a person's X variable on that person's Y variable
  - the effect of patients' depression on patients' quality of life
  - the effect of spouses' depression on spouses' quality of life

- Both members of the dyad have an actor effect.

Partner Effect

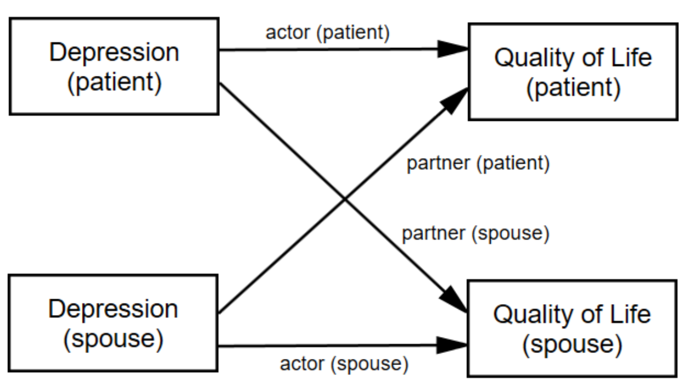
- Definition: The effect of a person's partner's X variable on the person's Y variable
  - the effect of patients' depression on spouses' quality of life
  - the effect of spouses' depression on patients' quality of life

- Both members of the dyad have a partner effect.

Distinguishability and the APIM

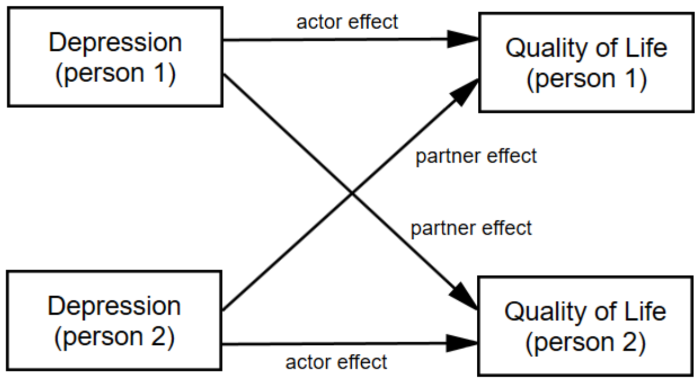
- Distinguishable dyads
  - Two actor effects
    - An actor effect for patients and an actor effect for spouses
  - Two partner effects
    - A partner effect from spouses to patients and a partner effect from patients to spouses

Distinguishable Dyads



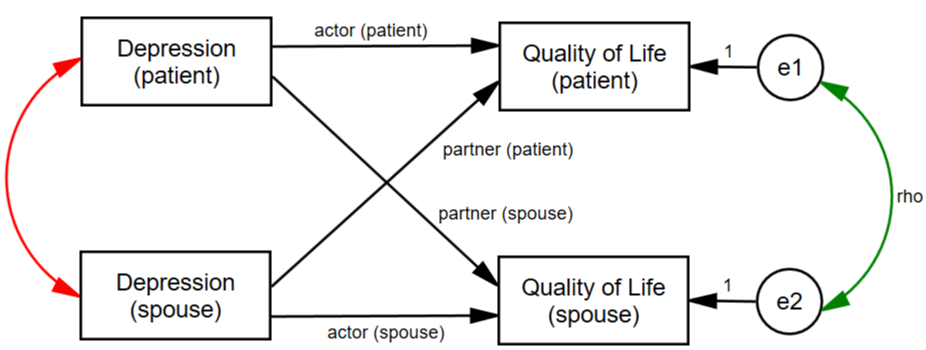
- Errors not pictured (but important)
- *The partner effect is fundamentally dyadic.* A common convention is to refer to it by the outcome variable. Researcher should be clear!

Indistinguishable Dyads



- The two actor effects are set to be equal and the two partner effects are set to be equal.

Nonindependence in the APIM



- Green curved line: Nonindependence in Y
- Red curved line: X as a mixed variable (r cannot be 1 or -1)
- Note that the combination of actor and partner effects explain some of the nonindependence in the dyad.

R DEMO

TEST OF DISTINGUISHABILITY

Test of Distinguishability

- Advantages of Treating Dyad Members as Indistinguishable
  - Simpler model with fewer parameters
  - More power in tests of actor and partner effects

- Disadvantages of Treating Dyad Members as Indistinguishable
  - If distinguishability makes a difference, then the model is wrong.
  - Sometimes the focus is on distinguishing variable and it is lost.
  - Some editors or reviewer will not allow you to do it.

Test of Distinguishability

- Four ways that dyads can be distinguishable
  1. Intercepts (main effect of distinguishing variable)
  2. Actor effects
  3. Partner effects
  4. Error variances

Test of Distinguishability

- Two runs:
- Distinguishable (either interaction or two-intercept, results are the same)
  - Different Actor and Partner Effects
  - Main Effect of Distinguishing Factor
  - Heterogeneity of Variance (CSH)
- Indistinguishable (4 fewer parameters)
  - Same Actor and Partner Effects
  - No Main Effect of Distinguishing Factor
  - Homogeneity of Variance (CSR)

Test of Distinguishability

- Run using ML, not REML
- Note the number of parameters
  - There should be 4 more than for the distinguishable run.
- Note the -2LogLikelihood (deviance)
- Subtract the deviances and number of parameters to get a χ^2 with 4df
- **Conclusion:** If χ^2 is not significant, then the data are consistent with the null hypothesis that the dyad members are indistinguishable. If however, χ^2 is significant, then the data are inconsistent with the null hypothesis that the dyad members are indistinguishable (i.e., dyad members are distinguishable in some way).

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BINARY AND COUNT OUTCOME VARIABLES

Generalized Linear Mixed Models

Generalized Linear Models

- In general we wrap the response variables in a link function (log, logit, probit, identity, etc.).
- For example
  - A logistic regression is a generalized linear model making use of a logit link function.
  - A log-linear of Poisson regression is a generalized linear model making use of a log link function.
  - A regression model is a generalized linear model making use of an "identity" link function—the response is multiplied by 1.

Logistic Regression Review

- DV is dichotomous
  - probability of belonging to group 1: P_1
  - probability of belonging to group 0: $P_0 = 1 - P_1$.
  - There are only two choices!

Odds and Odds Ratios

		committed Committed to Hospital		Total
		0 No	1 Yes	
minority Minority Classification	0 No	138	120	258
	1 Yes	54	42	96
Total		192	162	354

- **Probability** of being committed = $\frac{162}{354} = .458$
- **Odds** of being committed = $\frac{.458}{1-.458} = .845$
  - Odds of being committed for minorities = $\frac{.438}{1-.438} = .778$
  - Odds of being committed for non-minorities = $\frac{.465}{1-.465} = .870$
- Odds ratio for non-minorities vs. minorities = $\frac{.870}{.778} = 1.118$

  "Non-minorities are **1.118** times more likely to be committed than minorities."

Logistic Regression Equation

$$\ln\left(\frac{\widehat{P_1}}{1-\widehat{P_1}}\right) = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n$$

- Where $\widehat{P_1}$ is the predicted probability of being in group coded as 1
- $\frac{\widehat{P_1}}{1-\widehat{P_1}}$ is the odds of being in group 1
- $\ln\left(\frac{\widehat{P_1}}{1-\widehat{P_1}}\right)$ is the "logit" function

Logistic Regression Equation

$$\ln\left(\frac{\widehat{P_1}}{1-\widehat{P_1}}\right) = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n$$

- The b's are interpreted as the increase in log-odds of being in the target group for 1-unit increase in X.
- Exp(b) is the increase in odds for 1 unit increase in X—this works out to the odds ratio between X = a and X = a+1.

Log-Linear (Poisson) Regression Equation

- Used when the response variable is a count (e.g., number of cigarettes smoked per day).

$$\ln(Y) = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n$$

- Where $\boldsymbol{Y}$ is the response vairable
- $\boldsymbol{ln}(\boldsymbol{Y})$ is the "log" link function
- $\boldsymbol{b_1}$ is interpreted as the increase in log-Y for every increase in $\boldsymbol{X_1}$
- **Exp($\boldsymbol{b_1}$)** is interpreted in the usual way—as in the general linear model.

Generalized Mixed Linear Models

- Generalized linear models
  - In general we wrap the response in a link function (log, logit, probit, identity, etc.).
- Generalized Mixed Linear Models
  - Do the same, include a link function that is appropriate for your response, but then include random effects in the model.
  - "Mixed" refers to the mixture of fixed and random effects in the model.
- We'll fit these models with the `lme4` package in R, specifically, the `glmer()` function.

Generalized Estimating Equations (GEE)

- Nonindependence treated as a "nuisance" to be removed; no statistical tests of nonindependence
- Can be extended to:
  - Binomial outcome
  - Multinomial outcome (Categories: home/work/leisure)
  - Count data (Poisson, negative binomial)
  - Can also be used for continuous outcomes (normal distribution)
- Fit these models with the `gee` package in R, specifically, the `gee()` function.

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