**ANALYZING INTENSIVE LONGITUDINAL DATA (AILD)**

**Tilburg University**
**December 13 - 17, 2021**

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**Columbia University**

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**University of Delaware**

# Daily Schedule

**Morning:**

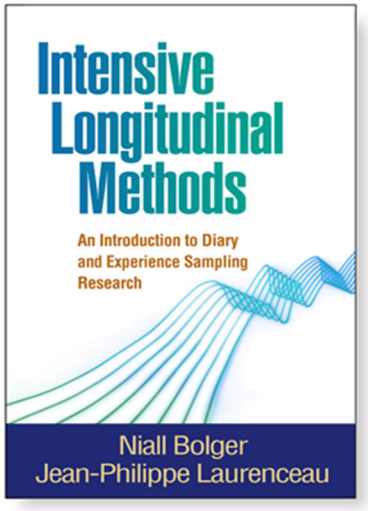
9:00a-10:10a: Lecture (70 min)
10:10a-10:25a: Break (15 min)
10:25a-11:25p: Lecture (60 min)
11:25a-11:40p: Break (15 min)
11:40a-12:30p: Lecture (50 min)

12:30a-1:30p: LUNCH (60 min)

**Afternoon:**

1:30p-2:40p: Lecture (70 min)
2:40p-2:55: Break (15 min)
2:55p-3:55p: Lecture (60 min)
3:55p-4:10p: Break (15)
4:10p-5:00p: Lecture (50 min)

# Bolger & Laurenceau (2013)




**Guilford Press *Methodology in the Social Sciences* Series**

**www.intensivelongitudinal.com**



# Workshop Dropbox Folder

https://tinyurl.com/AILD2021-Tilburg

# Workshop Overview

I. Overview and Introduction to Intensive Longitudinal (IL) Methods
II. Time Course Model for Continuous Outcomes
III. Within-Subject Causal Process Model for Continuous Outcomes
IV. Fundamental Guidelines for Modeling IL Data
V. Within-Subject Process Model for Categorical Outcomes
VI. Psychometrics of IL Data
VII. Within-Subject Mediation
VIII. Causal Process Model for Dyadic IL Data
IX. Future Modeling Extensions of IL Data

# Chapter 1

## Introduction to Intensive Longitudinal Methods

## What are Intensive Longitudinal Methods?

- **Intensive Longitudinal Methods** refer to a set of procedures that allow respondents to document their thoughts, feelings, and actions outside the walls of a laboratory
- Often resulting in repeated sampling in natural, everyday environments



## Methodological Motivation

**"Psychology needs to concern itself with life as it is lived."** *~Gordon Allport, 1942*

- The uniqueness of the individual
- Importance of the immediate context

# Hamaker and Wichers (2017)

Publications using "experience sampling," "ambulatory assessment," "ecological momentary assessment," or "daily diary"

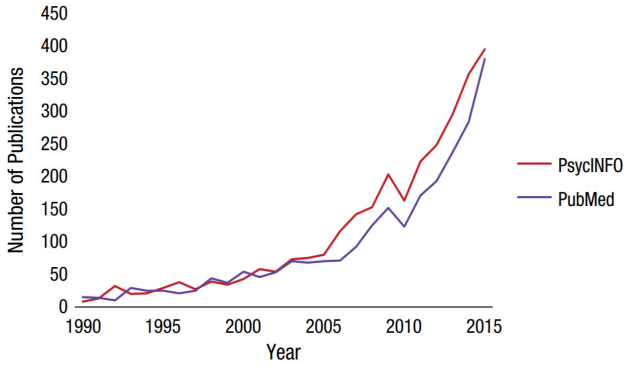



**Fig. 1.** Annual number of publications, based on searches using the PsycINFO and PubMed databases, with one or more of the following terms in the title, in the abstract, or as a keyword: *daily diary, experience sampling, ambulatory assessment, ecological momentary assessment*. Note that these are most likely underestimates of the actual numbers of studies based on intensive longitudinal data.



# A Major Source of Intensive Longitudinal Data

# Increasing Ability to Observe Behavior

Nike Fuel Band

Smart Shoe

Smart pedometers
http://www.kickstarter.com/projects/597507018/pebble-e-paper-watch-for-iphone-and-android

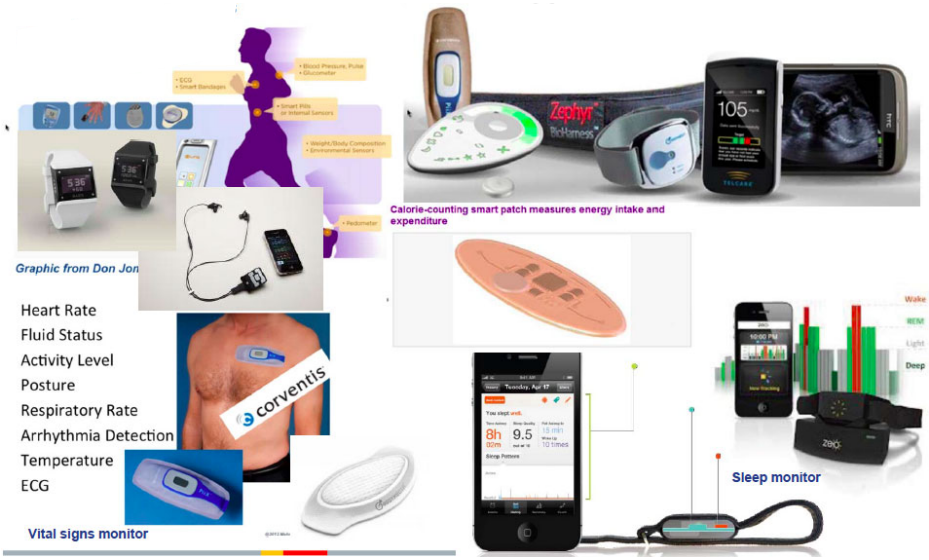
Baolab tennis racket

94Fifty sensor basketball

Smart surfboard with GPS and IMU



# Increasing Ability to Observe Behavior




Graphic from Don Jon

Calorie-counting smart patch measures energy intake and expenditure

Vital signs monitor

Sleep monitor

## Intensive Longitudinal Methods

- An ***intensive longitudinal study*** is one with enough repeated measurements to model a distinct change process for each ***individual***
- ***Within-person variability*** is key
- Time scale*:* ***minutes, hours, days, and weeks*** rather than months and years
- Used to understand people's thoughts, feelings, and behaviors ***in situ***



## Behavioral and Social Processes *in situ*…

- Although laboratory studies are powerful for theory testing, there are practical, ethical, and ecological limitations in their use
- Laboratory studies document what *can* happen…
- ILMs can document what *does* happen

## Strengths of Intensive Longitudinal Designs

- ILDs can…
  - Document that certain processes actually occur in everyday life
  - Examine how varying contexts/situations influence daily affect, cognition, and behavior
  - Minimize (or eliminate) retrospective bias
  - Focus on within-person changes versus between-person differences
  - Provide daily process data that complement macro-level longitudinal designs



## Prototypical Research Questions

A. How does the **typical person change over time** and how much do **people differ from one another in that change?**

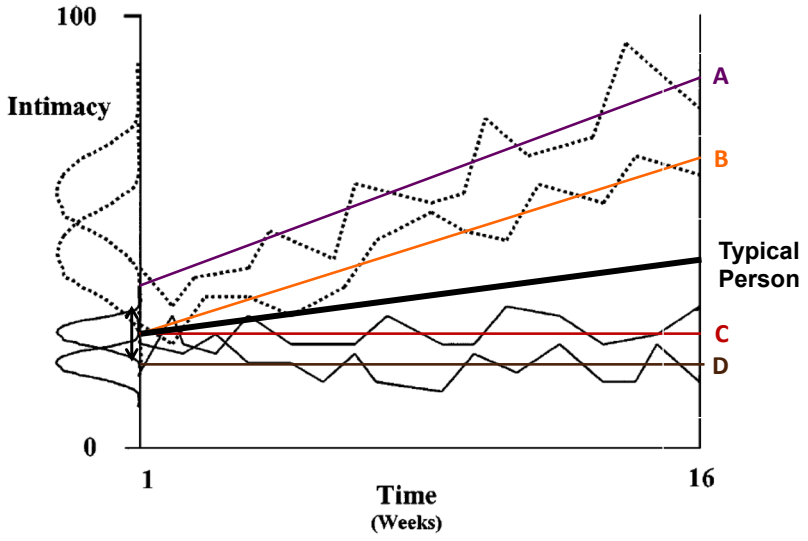
B. What is the **within-person process** for the **typical person** and how do **people differ from each other in these processes?**

# Research Questions

- There are two types of research questions that guide the vast majority of analyses of IL data:
  - The first concerns tracing the course of within-person change in an outcome for the average (typical) person, capturing how much people differ from each other in that change (heterogeneity), and whether these individual differences can be modeled with person-level variables



# A. Within-Person Change

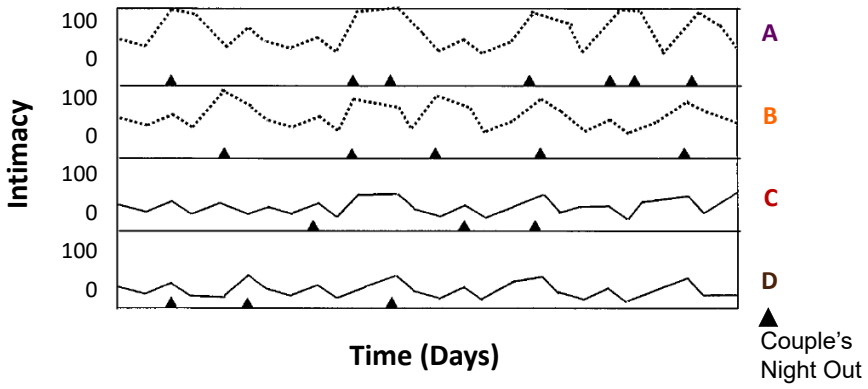


# Research Questions

- There are two types of research questions that guide the vast majority of analyses of IL data:
  - The second concerns identifying the within-person process (involving a predictor that unfolds over time) for the typical person, capturing heterogeneity in this process, and modeling the heterogeneity
- Often, there a situations where we would like to combine features of these two questions in the same model (we will see examples of this later in the workshop)



# B. Within-Person Process



## ILD are a Special Case of Multilevel Data

- Models for multilevel data go by many names:
  - Mixed Models
  - Mixed Effects Regression Models
  - Random Coefficient Modeling
  - Hierarchical Linear Modeling



## Examples of Multilevel Data Structures

- All multilevel data involve **nesting**, with micro-units (Level-1) nested within macro-units (Level-2):
  - Students in classrooms
  - Clients in therapists
  - Patients in wards
  - Repeated measurements within persons

## What is Different About Longitudinal Data?

- There is nesting of observations, but there is also a **strict ordering by time**
- Observation 1 precedes observation 2, and so on
- There is no such ordering for children in classrooms and many other multilevel data examples
- For some types of ILD, where the times of observations are fixed across time and across subjects, we can treat time as **crossed** not nested
  - e.g., in daily diary studies, day 1, day 2, day 3 have a common meaning across subjects



## Structuring of Intensive Longitudinal Data

- Intensive longitudinal data can be structured in one of two forms:
  - **Multivariate,** where columns comprise each repeated measure of a variable and rows comprise participants (aka WIDE)
  - **Univariate,** where columns comprise variables and rows comprise repeated measurements (within participants) (aka LONG)
  - The univariate form is the most useful for modeling ILD

| id | gender | BLdepression | Health1 | Health2 | Health3 | Health4 |
|---|---|---|---|---|---|---|
| 1.00 | 1.00 | 9.00 | 2.10 | 2.90 | 4.50 | 4.50 |
| 2.00 | .00 | 9.00 | 2.30 | 4.50 | 4.20 | 4.60 |
| 3.00 | .00 | 10.00 | 2.30 | 3.80 | 4.30 | 6.20 |
| 4.00 | 1.00 | 8.00 | 1.80 | 2.60 | 4.10 | 4.00 |
| 5.00 | 1.00 | 10.00 | 3.50 | 4.80 | 5.80 | 7.50 |

WIDE
or MULTIVARIATE

LONG
or
UNIVARIATE

| id | gender | BLdepression | Index1 | Health |
|---|---|---|---|---|
| 1.00 | 1.00 | 9.00 | 1 | 2.10 |
| 1.00 | 1.00 | 9.00 | 2 | 2.90 |
| 1.00 | 1.00 | 9.00 | 3 | 4.50 |
| 1.00 | 1.00 | 9.00 | 4 | 4.50 |
| 2.00 | .00 | 9.00 | 1 | 2.30 |
| 2.00 | .00 | 9.00 | 2 | 4.50 |
| 2.00 | .00 | 9.00 | 3 | 4.20 |
| 2.00 | .00 | 9.00 | 4 | 4.60 |
| 3.00 | .00 | 10.00 | 1 | 2.30 |
| 3.00 | .00 | 10.00 | 2 | 3.80 |
| 3.00 | .00 | 10.00 | 3 | 4.30 |
| 3.00 | .00 | 10.00 | 4 | 6.20 |
| 4.00 | 1.00 | 8.00 | 1 | 1.80 |
| 4.00 | 1.00 | 8.00 | 2 | 2.60 |
| 4.00 | 1.00 | 8.00 | 3 | 4.10 |
| 4.00 | 1.00 | 8.00 | 4 | 4.00 |
| 5.00 | 1.00 | 10.00 | 1 | 3.50 |
| 5.00 | 1.00 | 10.00 | 2 | 4.80 |
| 5.00 | 1.00 | 10.00 | 3 | 5.80 |
| 5.00 | 1.00 | 10.00 | 4 | 7.50 |



# Minimal Data Set

$ID_j$ Participant ID (1 to 5)
$T_i$ Time (0 to 4)
$X_{ij}$ Within predictor
$Y_{ij}$ Outcome
$W_j$ Between predictor

| $ID_j$ | $T_i$ | $X_{ij}$ | $Y_{ij}$ | $W_j$ |
|---|---|---|---|---|
| 1 | 0 | $x_{11}$ | $y_{11}$ | $w_1$ |
| 1 | 1 | $x_{21}$ | $y_{21}$ | $w_1$ |
| 1 | 2 | $x_{31}$ | $y_{31}$ | $w_1$ |
| 1 | 3 | $x_{41}$ | $y_{41}$ | $w_1$ |
| 1 | 4 | $x_{51}$ | $y_{51}$ | $w_1$ |
| 2 | 0 | $x_{12}$ | $y_{12}$ | $w_2$ |
| 2 | 1 | $x_{22}$ | $y_{22}$ | $w_2$ |
| 2 | 2 | $x_{32}$ | $y_{32}$ | $w_2$ |
| 2 | 3 | $x_{42}$ | $y_{42}$ | $w_2$ |
| 2 | 4 | $x_{52}$ | $y_{52}$ | $w_2$ |
| 3 | 0 | $x_{13}$ | $y_{13}$ | $w_3$ |
| 3 | 1 | $x_{23}$ | $y_{23}$ | $w_3$ |
| 3 | 2 | $x_{33}$ | $y_{33}$ | $w_3$ |
| 3 | 3 | $x_{43}$ | $y_{43}$ | $w_3$ |
| 3 | 4 | $x_{53}$ | $y_{53}$ | $w_3$ |
| 4 | 0 | $x_{14}$ | $y_{14}$ | $w_4$ |
| 4 | 1 | $x_{24}$ | $y_{24}$ | $w_4$ |
| 4 | 2 | $x_{34}$ | $y_{34}$ | $w_4$ |
| 4 | 3 | $x_{44}$ | $y_{44}$ | $w_4$ |
| 4 | 4 | $x_{54}$ | $y_{54}$ | $w_4$ |
| 5 | 0 | $x_{15}$ | $y_{15}$ | $w_5$ |
| 5 | 1 | $x_{25}$ | $y_{25}$ | $w_5$ |
| 5 | 2 | $x_{35}$ | $y_{35}$ | $w_5$ |
| 5 | 3 | $x_{45}$ | $y_{45}$ | $w_5$ |
| 5 | 4 | $x_{55}$ | $y_{55}$ | $w_5$ |

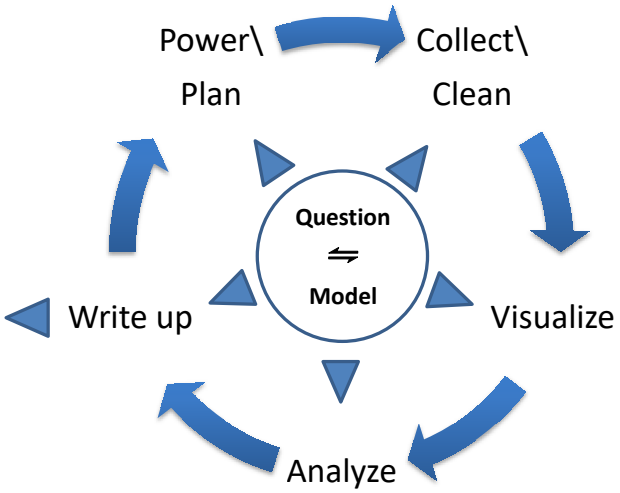
# Working with Multilevel Software

- **SPSS MIXED**
- SAS PROC MIXED
- **R lme4 package**
- Stata xtmixed
- HLM
- **Mplus**
- MLwiN

- We recommend being familiar with more than one program
- Each have specific strengths and weaknesses
- Replication across programs provides insight into the general modeling approach



# A Full Cycle Approach



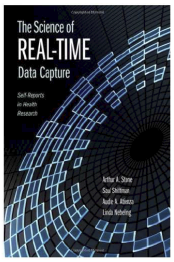
## Summary

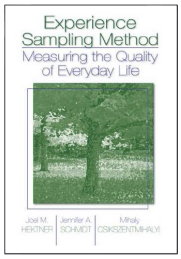
- We reviewed the full cycle approach and will be using it as a framework guiding learning the material in the first two chapters the workshop (Chapters 2 and 3)

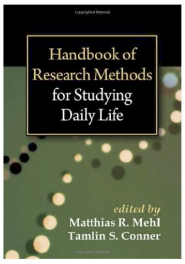


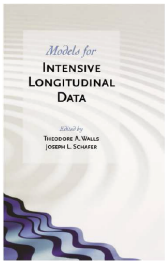
## Chapter Summary

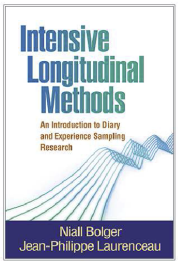
- Provided an overview of what will be covered in the 5-day workshop on **Analysis of Intensive Longitudinal Data**
- We provided a definition of ILMs and how a IL study is one with enough repeated measures to reliably capture a distinct change process for an individual
- Reviewed the strengths of ILMs, the basic research questions that can be addressed using IL data, issues of data structure
- Introduced a full cycle approach as a guiding framework






# Recommended Papers/Chapters


- Iida, M., Shrout, P. E., Laurenceau, J.-P., & Bolger, N. (2012). Using diary methods in psychological research. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf & K. J. Sher (Eds.), *APA handbook of research methods in psychology, Vol 1: Foundations, planning, measures, and psychometrics* (pp. 277-305). Washington, DC, US: American Psychological Association.

- Conner, T. S., Tennen, H., Fleeson, W. & Barrett, L. F. (2009). Experience sampling methods: A modern idiographic approach to personality research. *Social and Personality Psychology Compass, 3*, 292-313.

# Recommended Papers/Chapters (Con't)

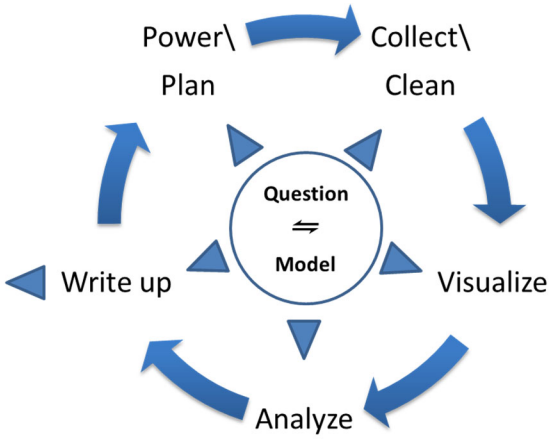
- Shiffman, S., Stone, A. A., & Hufford, M. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology, 4,* 1–32.
- Laurenceau, J.-P., & Bolger, N. (2005). Using diary methods to study marital and family processes. *Journal of Family Psychology, 19*, 86-97.
- Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology, 54*, 579-616.



# Chapter 2

**Modeling the Time Course of Continuous Outcomes (Latent Growth Curve Modeling)**

# A Full Cycle Approach






# Growth Example

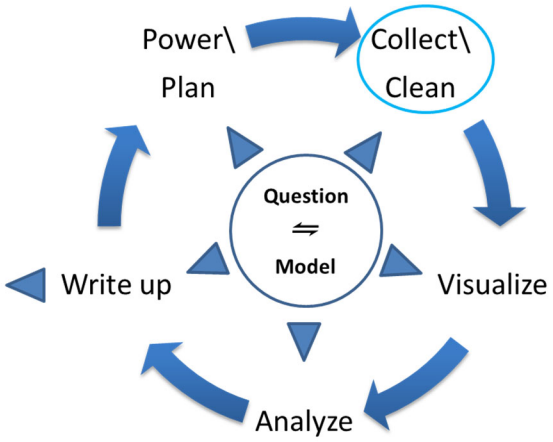
- A study of wives from 50 heterosexual married couples, randomly assigned to a 16-week martial therapy treatment condition or a 16-week waiting list control condition
- Dependent variable is $Y_{ij}$, the weekly intimacy score of wife $j$ (1 to 50) at time $i$ (Week 1 to Week 16)
- The single within-person independent variable is $T_{ij}$

# Research Questions

- What is the change in intimacy for the typical woman in the control group?
- For the typical woman in the treatment group?
- How much do women differ in their change within each group?
- To what extent does the treatment improve intimacy over the entire course of treatment?



# Collect Your Data/Clean Your Data



# Raw Intimacy Treatment Data Set

| ID | Week | Intimacy | Treatment |
|---|---|---|---|
| 1 | 0 | 2.96 | 0 |
| 1 | 1 | 2.34 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 1 | 14 | 1.15 | 0 |
| 1 | 15 | 4.54 | 0 |
| 2 | 0 | 0.64 | 0 |
| 2 | 1 | 3.1 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 2 | 14 | 0.65 | 0 |
| 2 | 15 | 2.21 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 25 | 0 | 3.09 | 0 |
| 25 | 1 | 2.59 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 25 | 14 | 4.9 | 0 |
| 25 | 15 | 2.1 | 0 |

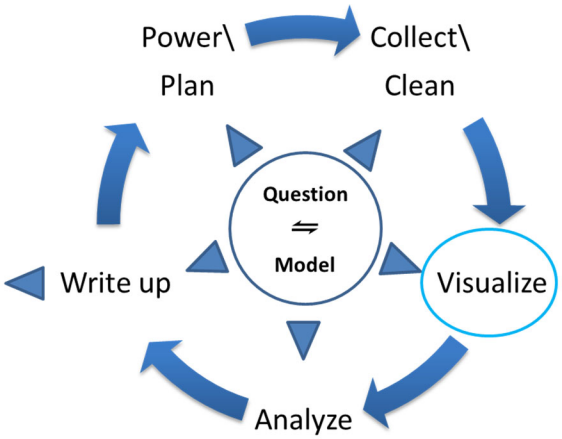
| ID | Week | Intimacy | Treatment |
|---|---|---|---|
| 26 | 0 | 1.8 | 1 |
| 26 | 1 | 2.5 | 1 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 26 | 14 | 3.46 | 1 |
| 26 | 15 | 3.78 | 1 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 50 | 0 | 1.47 | 1 |
| 50 | 1 | 4.17 | 1 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 50 | 14 | 3.01 | 1 |
| 50 | 15 | 3.54 | 1 |



# The Two Easiest Ways to Pick up Data Errors

- The first basic approach we recommend folks do upon obtaining the original raw dataset is to create a histogram of each variable of interest
  - Allows you to pick up out of range (i.e., impossible) values
  - Allows you to understand the distributional nature of each variable (particularly outcomes)
  - Allows you to get a sense of the amount of variability that exists for all variables
- The second is doing individual panel plots, which you will see in the next section of this chapter

# Visualize Before (and After) Analysis

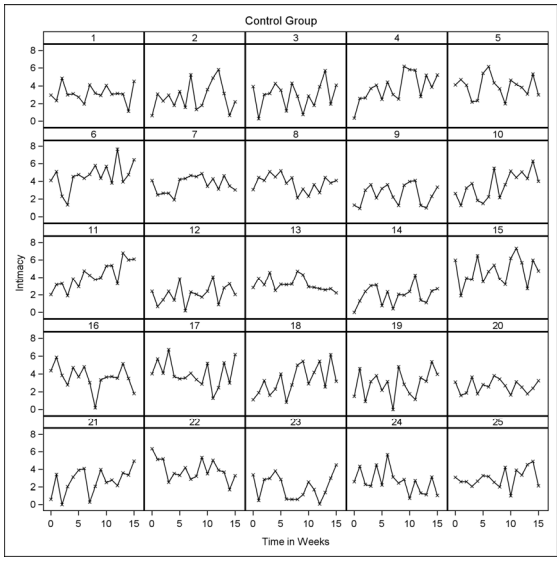





# Start with Individual Panel Plots

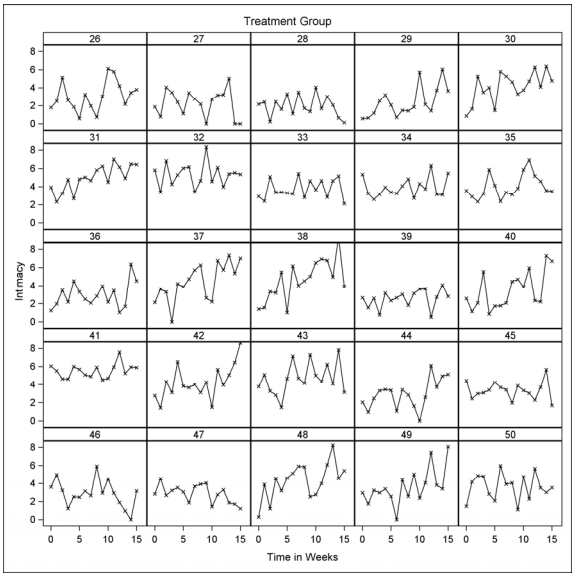
- First, plot the time series for each wife in the control group
- Then, plot the time series for each wife in the treatment group

# Panel Plot: Each Wife in the Control Group

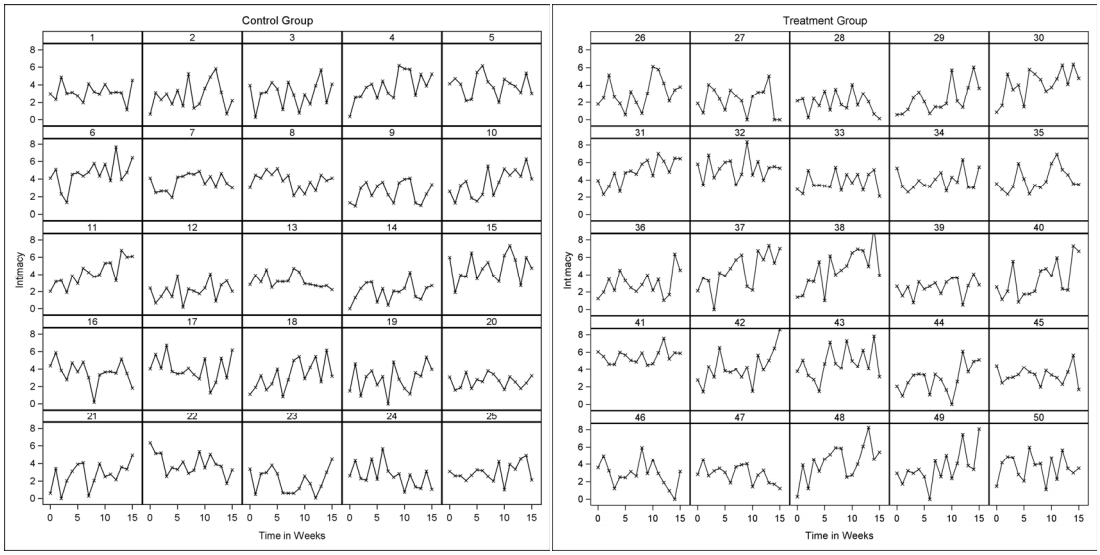





# Panel Plot: Each Wife in the Treatment Group

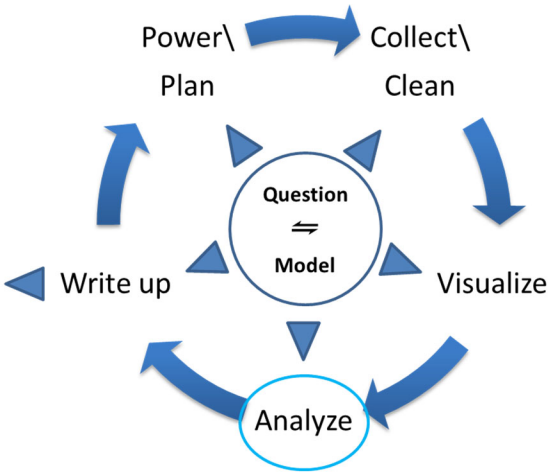


# A Bird's Eye View of All the Data

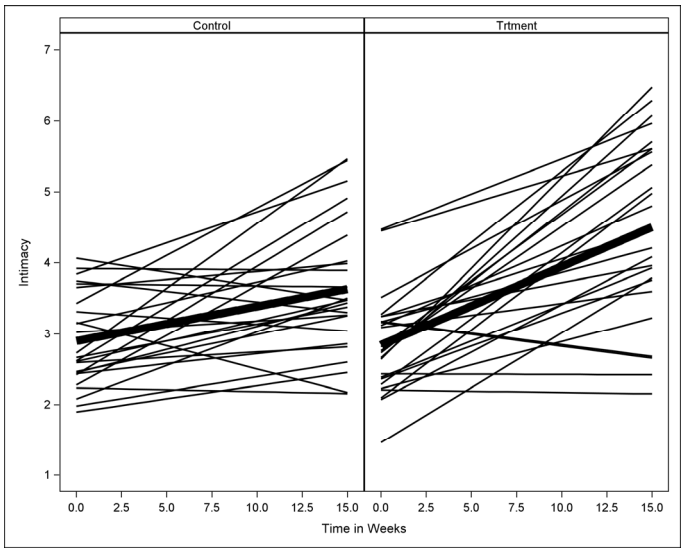





# **Analyze** Your Data



# Spaghetti Plot of Multilevel Modeling Results






# Multilevel Model Form

**Level 1:** $$Y_{ij} = \beta_{0j} + \beta_{1j} T_{ij} + \varepsilon_{ij}$$

**Level 2:** $$\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} W_j + u_{1j}$$

# From Multilevel to Mixed Model Form

**Level 2:**

$$\beta_{0j} = \boxed{\gamma_{00} + \gamma_{01}W_j + u_{0j}}$$

$$\beta_{1j} = \boxed{\gamma_{10} + \gamma_{11}W_j + u_{1j}}$$

**Level 1:**

$$Y_{ij} = \beta_{0j} + \beta_{1j}T_{ij} + \varepsilon_{ij}$$

$$Y_{ij} = \boxed{\gamma_{00} + \gamma_{01}W_j} + \beta_{1j}T_{ij} + \boxed{u_{0j}} + \varepsilon_{ij}$$

**Mixed Model:**

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \boxed{\gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij}} + u_{0j} + \boxed{u_{1j}T_{ij}} + \varepsilon_{ij}$$



# Mixed Model Notation

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij} + u_{0j} + u_{1j}T_{ij} + \varepsilon_{ij}$$

- *i* indexes time (weeks) and *j* indexes subject (wives)
- $Y_{ij}$ is the intimacy on week *i* for wife *j*
- $T_{ij}$ is the week *i* for wife *j*
- $W_j$ is the treatment group (0=control, 1 = treatment) for wife *j*

# Mixed Model Interpretation: Fixed Effects

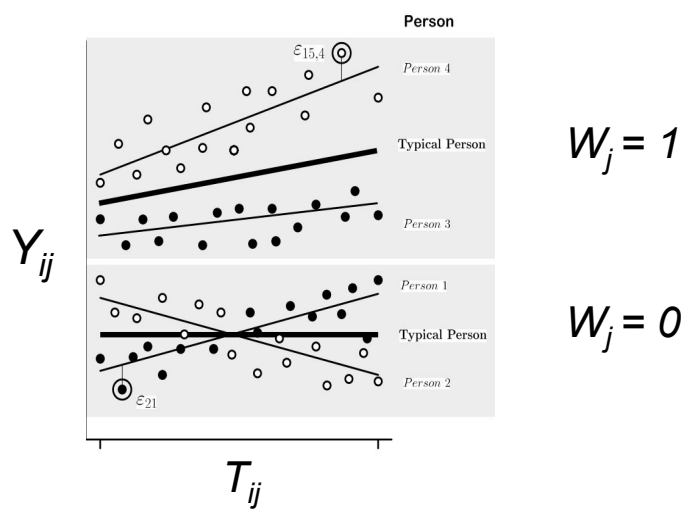
$$Y_{ij} = \boxed{\gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij}} + u_{0j} + u_{1j}T_{ij} + \varepsilon_{ij}$$

- $\gamma_{00}$ is the intimacy level of the control group at time 0
- $\gamma_{01}$ is how much higher or lower the treatment group's intimacy level is at time 0
- $\gamma_{10}$ is the change in intimacy per week for the control group
- $\gamma_{11}$ is how much higher or lower the rate of change for the treatment group is compared to the control group



# Graphical Summary For Four Persons

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij} + u_{0j} + u_{1j}T_{ij} + \varepsilon_{ij}$$



## Interpretation: Between-Person Random Effects

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij} + \boxed{u_{0j} + u_{1j}T_{ij}} + \varepsilon_{ij}$$

- Coefficients $u_{0j}$ and $u_{1j}$, known as between-person <u>random effects</u>, capture the (assumed-to-be) random deviations of individuals above or below their group average in terms of intercepts and slopes, respectively

$$Var\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} = \begin{bmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{bmatrix} = \mathrm{T}au$$



## Interpretation: Within-Person Random Effects

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij} + u_{0j} + u_{1j}T_{ij} + \boxed{\varepsilon_{ij}}$$

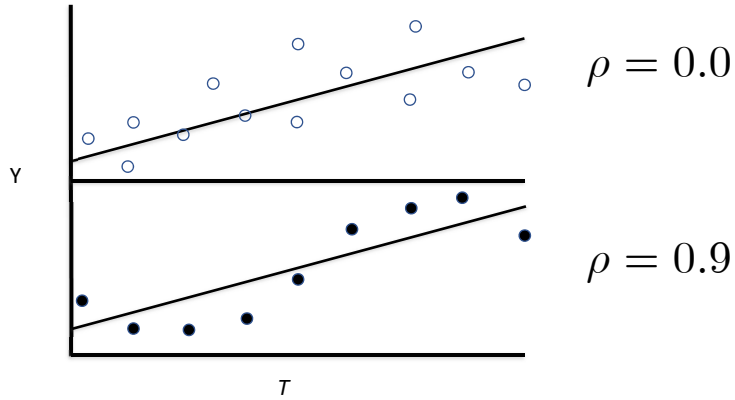
- There are also within-person random effects, the $\varepsilon_{ij}$'s, that capture the extent to which a woman's intimacy on a given week deviates above or below the value predicted by her specific regression line
- We could assume $\varepsilon_{ij}$'s are normally distributed random variables with a mean of zero and variance $\sigma^2$
- Usually with ILD, we allow for serial (auto-)correlation

$$\varepsilon_{ij} = \rho\varepsilon_{i-1,j} + v_{ij}$$

where $\varepsilon_{i-1,j}$ is the prior time point's residual and $v_{ij}$ is an additional well-behaved random residual

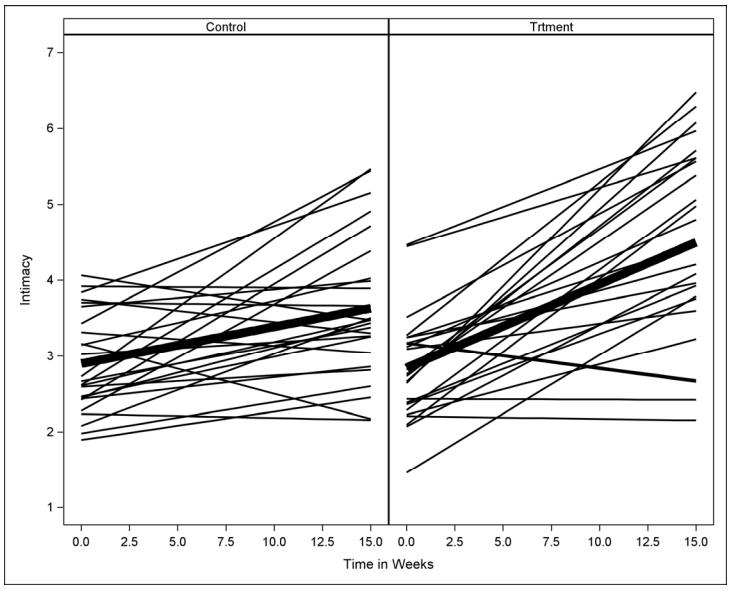
# Serial Correlation

- Depiction of non-autocorrelated residuals (upper panel) and positively autocorrelated residuals (lower panel)






# Spaghetti Plot of Multilevel Modeling Results



# APA Formatted Table of Time Course Results

*Estimates of Linear Growth Model Over 16 Weeks for Female Intimacy as a Function of Intervention Group (N=50).*

| Model parameters | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | 95% *CI* | |
| | Fixed effects (intercept, slopes) | Estimate (SE) | *t*(48) | *p* | Lower | Upper |
| $\gamma_{00}$ | Intercept (level at week 1) | 2.90 (0.21) | 14.00 | <0.001[a] | 2.48 | 3.32 |
| $\gamma_{10}$ | Time | 0.74 (0.35) | 2.12 | 0.039 | 0.04 | 1.43 |
| $\gamma_{01}$ | Group | -0.06 (0.29) | -0.19 | 0.848 | -0.65 | 0.53 |
| $\gamma_{11}$ | Group by time | 0.92 (0.49) | 1.88 | 0.067 | -0.07 | 1.91 |

| | | | | | 95% *CI*[d] | |
|---|---|---|---|---|---|---|
| | Random effects ((co-)variances) | Estimate (SE) | *Z* | *p* | Lower | Upper |
| | Level-2 (between-person) | | | | | |
| $\tau_{00}$ | Intercept | 0.69 (0.22) | 3.10 | 0.001 | 0.40 | 1.46 |
| $\tau_{11}$ | Time | 1.89 (0.62) | 3.04 | 0.001 | 1.09 | 4.09 |
| $\tau_{10}$ | Intercept & time | -0.52 (0.31) | -1.69 | 0.092 | -1.12 | 0.08 |
| | Level-1 (within-person) | | | | | |
| $\sigma_{\varepsilon}^{2}$ | Residual | 1.69 (0.09) | 18.37 | <0.001 | 1.53 | 1.89 |
| $\rho$ | Autocorrelation | 0.00 (0.04) | 0.00 | 0.999 | -0.08 | 0.08 |

Note: [a]All *p* values are two-tailed except in the case of variances, where one-tailed *p*-values are used (because variances are constrained to be non-negative). [b]Time is coded 0 = week 1, 1 = week 16, with equal intervals for the intervening weeks. [c]Group is coded 0 for the control group and 1 for the treatment group. [d]Confidence intervals for variances were computed using the Satterthwaite method (see Milliken et al, 2006).



# APA Formatted Table of Time Course Results

*Estimates of Linear Growth Model Over 16 Weeks for Female Intimacy as a Function of Intervention Group (N=50).*

| Model parameters | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | 95% *CI* | |
| Fixed effects (intercept, slopes) | | Estimate (SE) | *t*(48) | *p* | Lower | Upper |
| Intercept (level at week 1) | | 2.90 (0.21) | 14.00 | <0.001[a] | 2.48 | 3.32 |
| Time | | 0.74 (0.35) | 2.12 | 0.039 | 0.04 | 1.43 |
| Group | | -0.06 (0.29) | -0.19 | 0.848 | -0.65 | 0.53 |
| Group by time | | 0.92 (0.49) | 1.88 | 0.067 | -0.07 | 1.91 |

| | | | | | 95% *CI*[d] | |
|---|---|---|---|---|---|---|
| Random effects ((co-)variances) | | Estimate (SE) | *Z* | *p* | Lower | Upper |
| Level-2 (between-person) | | | | | | |
| | Intercept | 0.69 (0.22) | 3.10 | 0.001 | 0.40 | 1.46 |
| | Time | 1.89 (0.62) | 3.04 | 0.001 | 1.09 | 4.09 |
| | Intercept & time | -0.52 (0.31) | -1.69 | 0.092 | -1.12 | 0.08 |
| Level-1 (within-person) | | | | | | |
| | Residual | 1.69 (0.09) | 18.37 | <0.001 | 1.53 | 1.89 |

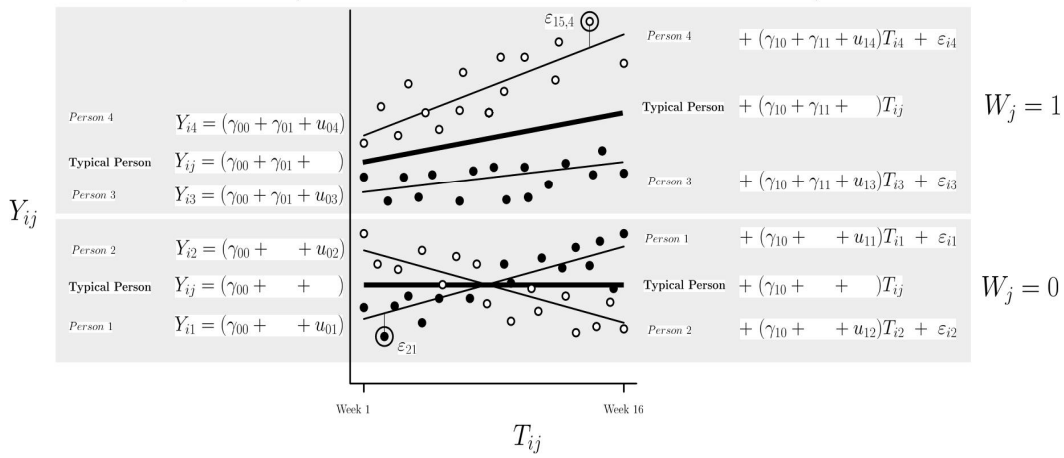
Note: [a]All *p* values are two-tailed except in the case of variances, where one-tailed *p*-values are used (because variances are constrained to be non-negative). [b]Time is coded 0 = week 1, 1 = week 16, with equal intervals for the intervening weeks. [c]Group is coded 0 for the control group and 1 for the treatment group. [d]Confidence intervals for variances were computed using the Satterthwaite method (see Milliken et al, 2006).

Note: Without autocorrelated residuals

# Four Persons with Fixed and Random Effects

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij} + u_{0j} + u_{1j}T_{ij} + \varepsilon_{ij}$$

| Person | Y | Intercepts | Person | Slopes | T | e |
|---|---|---|---|---|---|---|
| *Person 4* | $Y_{i4} = (\gamma_{00} + \gamma_{01} + u_{04})$ | | *Person 4* | $+ (\gamma_{10} + \gamma_{11} + u_{14})$ | $T_{i4}$ | $+ \varepsilon_{i4}$ |
| **Typical Person** | $Y_{ij} = (\gamma_{00} + \gamma_{01} + \quad)$ | | **Typical Person** | $+ (\gamma_{10} + \gamma_{11} + \quad)$ | $T_{ij}$ | |
| *Person 3* | $Y_{i3} = (\gamma_{00} + \gamma_{01} + u_{03})$ | | *Person 3* | $+ (\gamma_{10} + \gamma_{11} + u_{13})$ | $T_{i3}$ | $+ \varepsilon_{i3}$ |
| *Person 2* | $Y_{i2} = (\gamma_{00} + \quad + u_{02})$ | | *Person 1* | $+ (\gamma_{10} + \quad + u_{11})$ | $T_{i1}$ | $+ \varepsilon_{i1}$ |
| **Typical Person** | $Y_{ij} = (\gamma_{00} + \quad + \quad)$ | | **Typical Person** | $+ (\gamma_{10} + \quad + \quad)$ | $T_{ij}$ | |
| *Person 1* | $Y_{i1} = (\gamma_{00} + \quad + u_{01})$ | | *Person 2* | $+ (\gamma_{10} + \quad + u_{12})$ | $T_{i2}$ | $+ \varepsilon_{i2}$ |






# Working with SPSS

- Graphical exploration using panel plots
- Spaghetti Plots
- SPSS Mixed Modeling procedure
- A note about “shrinkage”

# Graphical Data Exploration using SPSS

- Panel plots
  - Outcome by time, paneled by id
  - Spaghetti plots (Before and after multilevel modeling)



# Link to SPSS GPL Graphics Manual

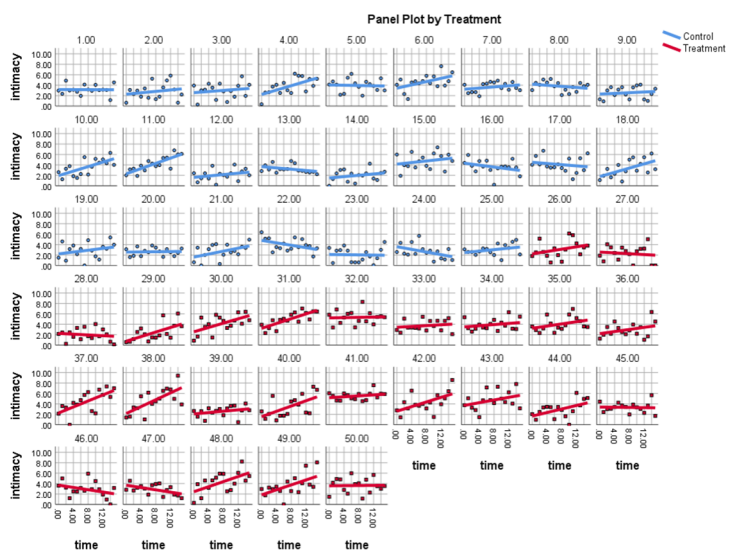
- IBM SPSS Statistics 26 Documentation
- SPSS GPL syntax is somewhat cumbersome but is the only way we know of how to have SPSS graph Panel Plots and Spaghetti Plots

# SPSS GPL Code for Panel Plots

```
*****************************************
*COMMENT: Panels by id (with both Tx in different colors).
*COMMENT: Note that individual lines *not* based on fitted multilevel model.

formats time intimacy (f4.2) treatment (f1.0).
GGRAPH
  /GRAPHDATASET NAME="GraphDataset" VARIABLES= intimacy time id treatment
  /GRAPHSPEC SOURCE=INLINE INLINETEMPLATE=["<setWrapPanels/>"].
BEGIN GPL
SOURCE: s=userSource( id( "GraphDataset" ) )
DATA: intimacy=col( source(s), name( "intimacy" ) )
DATA: time=col( source(s), name( "time" ) )
DATA: treatment=col(source(s), name("treatment"), unit.category() )
DATA: id=col( source(s), name( "id" ), unit.category() )
GUIDE: text.title( label( "Panel Plot by Treatment" ) )
GUIDE: axis( dim( 1 ), label( "time" ) )
GUIDE: axis( dim( 2 ), label( "intimacy" ) )
GUIDE: axis( dim( 3 ), label( "id" ), opposite() )
GUIDE: legend( aesthetic( aesthetic.shape.interior ), null() )
SCALE: linear( dim( 1 ), min( 0 ), max( 15 ) )
SCALE: linear( dim( 2 ), min( 0 ), max( 10 ) )
ELEMENT: point( position( time * intimacy * id ), shape.interior(treatment), color(treatment) )
ELEMENT: line( position(smooth.linear( time * intimacy  * id) ), shape.interior(treatment), color(treatment))
END GPL.
```



# SPSS Panel Plots

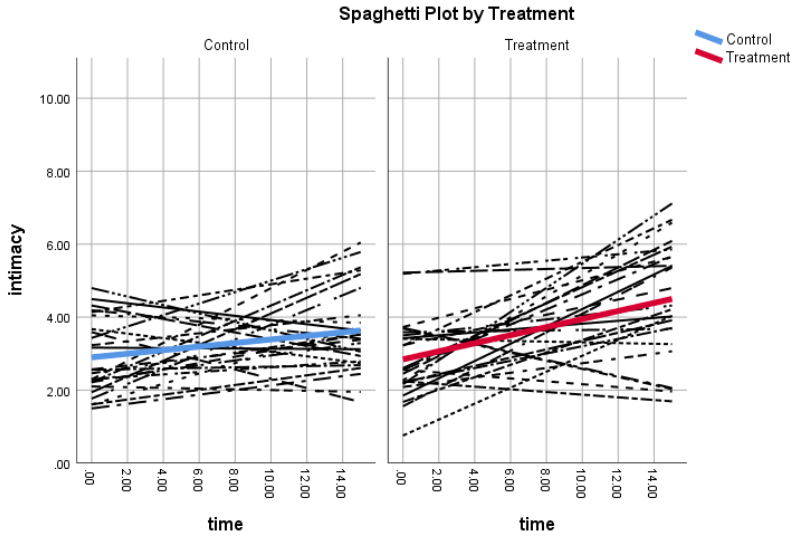


# SPSS GPL Code for Spaghetti Plots

```
*****************************************
*COMMENT: Spaghetti plots (male and female side-by-side panels) with solid fixed effects lines.
*COMMENT: Note that individual lines *NOT *based on fitted multilevel model.

GGRAPH
  /GRAPHDATASET NAME="GraphDataset" VARIABLES= intimacy time id treatment
  /GRAPHSPEC SOURCE=INLINE  INLINETEMPLATE=["<setWrapPanels/>"].
BEGIN GPL
SOURCE: s=userSource( id( "GraphDataset" ) )
DATA: intimacy=col( source(s), name( "intimacy" ) )
DATA: time=col( source(s), name( "time" ) )
DATA: id=col( source(s), name( "id" ), unit.category() )
DATA: treatment=col( source(s), name( "treatment" ), unit.category() )
GUIDE: text.title( label( "Spaghetti Plot by Treatment" ) )
GUIDE: axis( dim( 1 ), label( "time" ) )
GUIDE: axis( dim( 2 ), label( "intimacy" ) )
GUIDE: axis( dim( 3 ), label( "treatment" ), opposite() )
GUIDE: legend( aesthetic( aesthetic.shape.interior ), null() )
SCALE: linear( dim( 1 ), min( 0 ), max( 15 ) )
SCALE: linear( dim( 2 ), min( 0 ), max( 10 ) )
ELEMENT: line( position( smooth.linear( summary.mode( time * intimacy * treatment ) ) ), shape.interior( id ))
ELEMENT: line( position( smooth.linear( time * intimacy * treatment ) ), color(treatment) )
END GPL.
```



# Spaghetti Plot (Before Multilevel Modeling)



# SPSS MIXED code for Time Course Example

```
MIXED intimacy WITH time01 treatment
  /FIXED=time01 treatment time01*treatment | SSTYPE(3)
  /METHOD=REML
  /PRINT=G SOLUTION TESTCOV
  /RANDOM=INTERCEPT time01 | SUBJECT(id) COVTYPE(UN)
  /REPEATED=time | SUBJECT(id) COVTYPE(AR1).
```

timecourse-plots-and-mixed-spss-syntax.sps



# SPSS MIXED Output: Fixed Effects

*Estimates of Fixed Effects*[a]

| | Parameter | Estimate | Std. Error | df | t | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|---|
| $\gamma_{00}$ | Intercept | 2.898974 | .207030 | 47.975 | 14.003 | .000 | 2.482707 | 3.315242 |
| $\gamma_{10}$ | time01 | .735201 | .347199 | 47.998 | 2.118 | .039 | .037111 | 1.433292 |
| $\gamma_{01}$ | treatment | -.056442 | .292785 | 47.975 | -.193 | .848 | -.645134 | .532249 |
| $\gamma_{11}$ | time01 * treatment | .921436 | .491013 | 47.998 | 1.877 | .067 | -.065813 | 1.908686 |

a. Dependent Variable: Intimacy outcome.

# SPSS MIXED Output: Random Effects

*Estimates of Covariance Parameters*[a]

| Parameter | | | Estimate | Std. Error | Wald Z | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|---|
| Repeated Measures | $\sigma^2_\varepsilon$ | AR1 diagonal | 1.692482 | .092127 | 18.371 | .000 | 1.521216 | 1.883031 |
| | $\rho$ | AR1 rho | -.000034 | .042175 | -.001 | .999 | -.082507 | .082439 |
| Intercept + time01 [subject = id] | $\tau_{00}$ | UN (1,1) | .685773 | .221288 | 3.099 | .002 | .364344 | 1.290771 |
| | $\tau_{11}$ | UN (2,1) | -.516135 | .306251 | -1.685 | .092 | -1.116375 | .084105 |
| | $\tau_{10}$ | UN (2,2) | 1.893711 | .623774 | 3.036 | .002 | .992966 | 3.611547 |

a. Dependent Variable: Intimacy outcome.

*Random Effect Covariance Structure (G)*[a]

| | Intercept \| id | time01 \| id |
|---|---|---|
| Intercept \| id | .685773 | -.516135 |
| time01 \| id | -.516135 | 1.893711 |

Unstructured

a. Dependent Variable: Intimacy outcome.



# SPSS MIXED

```
MIXED intimacy WITH time01 treatment
  /FIXED=time01 treatment time01*treatment | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT time01 | SUBJECT(id) COVTYPE(UN)
  /REPEATED=time | SUBJECT(id) COVTYPE(AR1)
  /SAVE = FIXPRED(FIXED) PRED(BLUP).
```

**Note: BLUP = Best Linear Unbiased Predictions**

timecourse-plots-and-mixed-spss-syntax.sps

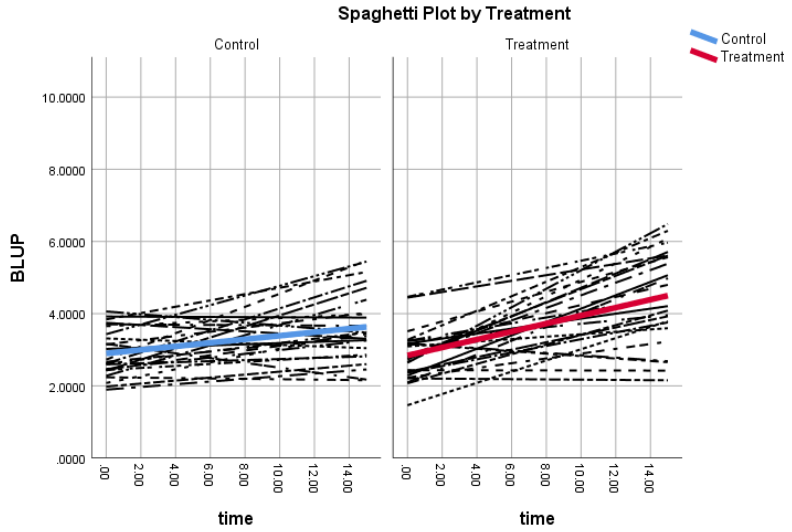
# Predicted Values for Plotting

| id | time | time01 | intimacy | treatment | FIXED | BLUP |
|---|---|---|---|---|---|---|
| 1.00 | .00 | .00 | 2.96 | 0 | 2.8990 | 3.0224 |
| 1.00 | 1.00 | .07 | 2.34 | 0 | 2.9480 | 3.0386 |
| 1.00 | 2.00 | .13 | 4.88 | 0 | 2.9970 | 3.0548 |
| 1.00 | 3.00 | .20 | 2.99 | 0 | 3.0460 | 3.0710 |
| 1.00 | 4.00 | .27 | 3.13 | 0 | 3.0950 | 3.0872 |
| 1.00 | 5.00 | .33 | 2.73 | 0 | 3.1440 | 3.1034 |
| 1.00 | 6.00 | .40 | 1.96 | 0 | 3.1931 | 3.1196 |
| 1.00 | 7.00 | .47 | 4.13 | 0 | 3.2421 | 3.1358 |
| 1.00 | 8.00 | .53 | 3.17 | 0 | 3.2911 | 3.1520 |
| 1.00 | 9.00 | .60 | 2.93 | 0 | 3.3401 | 3.1683 |
| 1.00 | 10.00 | .67 | 4.07 | 0 | 3.3891 | 3.1845 |
| 1.00 | 11.00 | .73 | 3.06 | 0 | 3.4381 | 3.2007 |
| 1.00 | 12.00 | .80 | 3.14 | 0 | 3.4871 | 3.2169 |
| 1.00 | 13.00 | .87 | 3.09 | 0 | 3.5361 | 3.2331 |
| 1.00 | 14.00 | .93 | 1.15 | 0 | 3.5852 | 3.2493 |
| 1.00 | 15.00 | 1.00 | 4.54 | 0 | 3.6342 | 3.2655 |
| 2.00 | .00 | .00 | .64 | 0 | 2.8990 | 2.4660 |
| 2.00 | 1.00 | .07 | 3.10 | 0 | 2.9480 | 2.5188 |
| 2.00 | 2.00 | .13 | 2.31 | 0 | 2.9970 | 2.5715 |
| 2.00 | 3.00 | .20 | 2.97 | 0 | 3.0460 | 2.6243 |
| 2.00 | 4.00 | .27 | 1.81 | 0 | 3.0950 | 2.6770 |
| 2.00 | 5.00 | .33 | 3.38 | 0 | 3.1440 | 2.7298 |
| 2.00 | 6.00 | .40 | 1.57 | 0 | 3.1931 | 2.7825 |
| 2.00 | 7.00 | .47 | 5.24 | 0 | 3.2421 | 2.8353 |

- Columns added to dataset for plotting
- "FIXED" column contains predicted values based fixed effect coefficient estimates
- "BLUP" column contains predicted values based on both fixed effect and random effect coefficient estimates

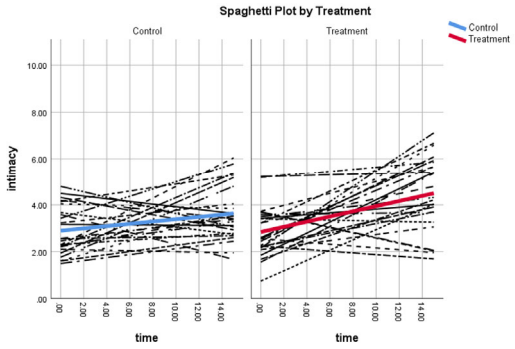


# Spaghetti Plot (Based on Multilevel Model)

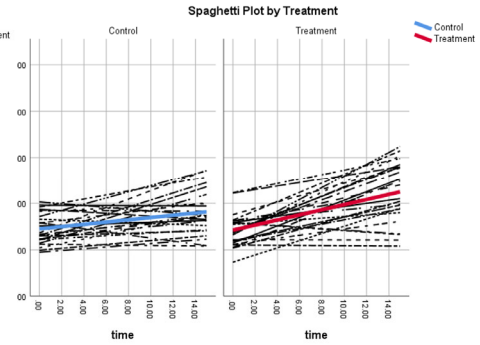


# Visualizing Shrinkage

**OLS-based Predictions**




**Multilevel-based Predictions**






# Multilevel Modeling and Shrinkage

- There is no common distribution assumed for the individual OLS slopes
- Each OLS slope has sampling variability and the collective effect of that is to “push” these slopes further apart than they really are
- The multilevel model assumes that the individual intercepts and slopes come from a bivariate normal distribution and this is used to “shrink” them toward the mean of that distribution

# Working with R

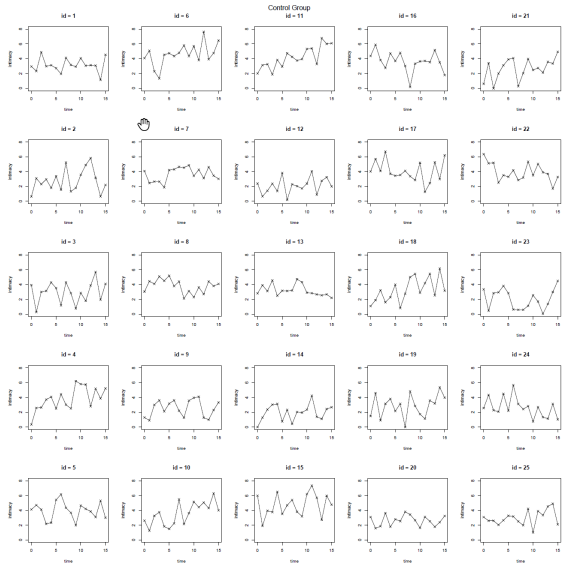
- Graphical exploration with panel plots
- Spaghetti plots
- Mixed modeling in R using *nlme*



# R Code for Panel Plots

```
##############################################################
#Read a csv file containing the data
time <- read.csv(here('time.csv'))
##############################################################

##############################################################
#Figure 4.2: Panel plots for Control Group

par(mfcol=c(5,5))
for (i in 1:25){
  plot(time$time[time$id==i], time$intimacy[time$id==i],
       ylab="intimacy", xlab="time", type="l", lwd=2, pch=4,
       ylim=c(0,8), main=paste("id =", i, sep = " "))
}
mtext("Control Group", side=3, outer=TRUE, line=-1.2)
##############################################################
```

# Panel Plot in R for Control Group

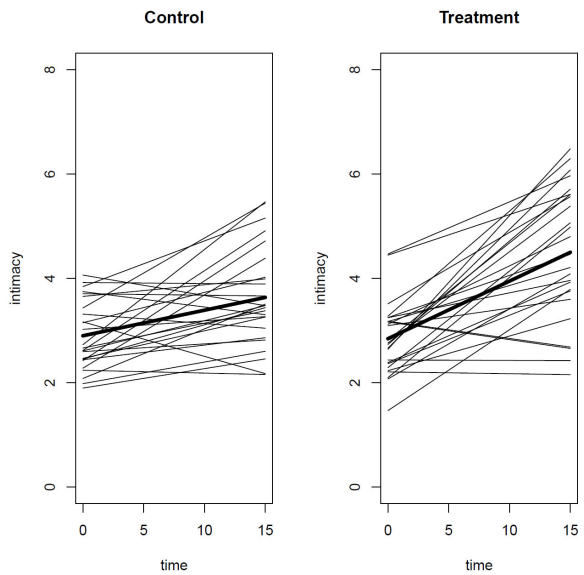





# Spaghetti Plot R Code (using model predictions)

```
##################################################################################
#Figure 4.5: Spaghetti Plots for Control Group and Treatment Group
par(mfcol=c(1,2))
plot(time$time[time$treatment==0], time$intimacy[time$treatment==0],
     ylab="intimacy", xlab="time", type="n", pch=4, ylim=c(0,8), main="Control")
for (i in 1:25){
  lines(time$time[time$id==i], fitted(lgmodel)[time$id==i])
}
predc<-2.8989745 + ((0.7352012)/15)*time$time
lines(time$time, predc, lwd=4)


plot(time$time[time$treatment==1], time$intimacy[time$treatment==1],
     ylab="intimacy", xlab="time", type="n", pch=4, ylim=c(0,8), main="Treatment")
for (i in 26:50){
  lines(time$time[time$id==i], fitted(lgmodel)[time$id==i])
}
predt<-(2.8989745 - 0.0564426) + ((0.7352012 + 0.9214365)/15)*time$time
lines(time$time, predt, lwd=4)
##################################################################################
```

# Spaghetti Plot in R (using model predictions)






# Modeling of Time Course Data: *nlme* in R

```
##########################################################################################
#Run linear growth model with AR(1) errors
lgmodel <- lme(fixed=intimacy ~ time01*treatment, data=time, random=~time01 | id, correlation = corAR1())
summary(lgmodel)
##########################################################################################
```

# Modeling of Time Course Data: *nlme* in R

```
> summary(lgmodel)
Linear mixed-effects model fit by REML
 Data: time
       AIC      BIC    logLik
  2852.392 2894.508 -1417.196

Random effects:
 Formula: ~time01 | id
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev    Corr
(Intercept) 0.8281209 (Intr)
time01      1.3761434 -0.453
Residual    1.3009532

Correlation Structure: AR(1)
 Formula: ~1 | id
 Parameter estimate(s):
           Phi
-3.601108e-05
Fixed effects: intimacy ~ time01 * treatment
                     Value Std.Error  DF   t-value p-value
(Intercept)       2.8989745 0.2070310 748 14.002607  0.0000
time01            0.7352012 0.3472019 748  2.117504  0.0345
treatment        -0.0564426 0.2927861  48 -0.192777  0.8479
time01:treatment  0.9214365 0.4910176 748  1.876586  0.0610
 Correlation:
                  (Intr) time01 trtmnt
time01            -0.599
treatment         -0.707  0.423
time01:treatment  0.423 -0.707 -0.599

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-2.62425713 -0.67979280 -0.01899203  0.64336207  2.44625355

Number of Observations: 800
Number of Groups: 50
```



# Brief Mplus Tutorial

- Basics of Mplus modeling syntax
- Example of multiple regression in Mplus

# Brief Mplus Tutorial

- Mplus is a flexible program for structural equation models, multilevel models, and related techniques
- Uses SEM type syntax and specifications
- Runs input files (extension *.inp) and returns output files (extension *.out) with several output options
- www.statmodel.com (Muthén & Muthén)



# Mplus Syntax Basics

- The basic Mplus commands include:
  - TITLE: (Any title you wish)
  - DATA: (Path to the data file)
  - VARIABLE: (Names and types of variables)
  - ANALYSIS: (Specify analysis type and estimator)
  - MODEL: (Where you specify your model)
  - OUTPUT: (Select options included in output)
- An "!" comments out code in green
- All lines must end with a semicolon (;) like SAS

## Mplus Syntax Basics

- Mplus models are built by specifying relationships between variables
- The general structure is:
  *Variable* RELATIONSHIP *Variable* (label);
- The label is optional and is of use for setting parameter constraints as for actual labeling
- Parameters with the same labels are constrained to be equivalent



## "Relationships" in Mplus

- WITH (covariance or correlation)
- ON (regression)
- BY (loading)

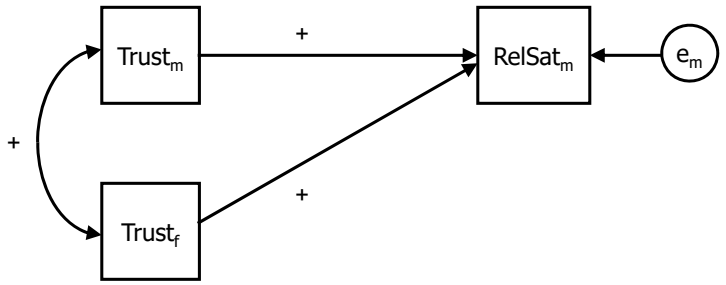
Note: In our code, we try to keep Mplus commands and options in CAPS and user input in lower case

# Description of Multiple Regression Example

- Data come from a study of 90 heterosexual newlywed couples
- For this example, we use cross-sectional scores from both male and female partners on relationship satisfaction (outcome) and trust (predictor) based on multi-item measures
- Specifically, we posit a model where male partner ***RelSat*** is regression on male and female partner ***Trust***



# Linear Regression Example



# Mplus Syntax for Regression Example

```
TITLE:    Cross-sectional Regression Model;
DATA:     FILE = relsat.txt; !Note that can also include path to data
VARIABLE:  NAMES = mrelsat1 frelsat1 mrelsat2 frelsat2 mtrust1 ftrust1;
          USEVAR = mrelsat1 mtrust1 ftrust1;
DEFINE:   CENTER mtrust1 ftrust1 (GRANDMEAN);
ANALYSIS:  TYPE = GENERAL;
MODEL:    mrelsat1 ON mtrust1 ftrust1;
OUTPUT:   SAMPSTAT CINTERVAL STDYX;
PLOT:     TYPE=PLOT1; !For basic histograms and scatterplots

!Exclamation point indicates a comment
```

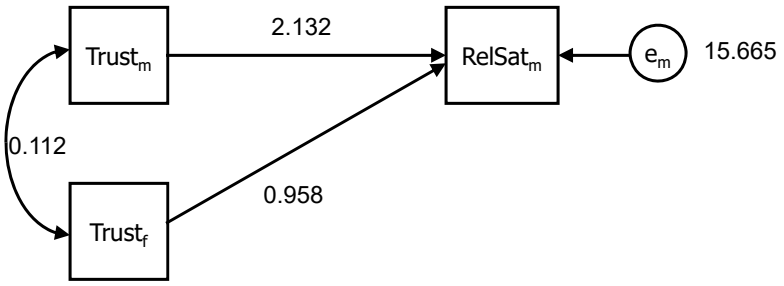
relsatmplus.inp



# Mplus Output: relsatmplus.out

```
MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

 MRELSAT1 ON
    MTRUST1            2.132      0.544      3.921      0.000
    FTRUST1            0.958      0.560      1.710      0.087

 Intercepts
    MRELSAT1          30.852      0.417     73.951      0.000

 Residual Variances
    MRELSAT1          15.664      2.335      6.708      0.000
```

# Regression Example: Unstandardized Estimates






# Working with Mplus: Multilevel Modeling

- Warning on Mplus: No AR1 residual structure using ML estimation
- Modeling Time Course example using Mplus
- Comparing Time Course example output across Mplus, SPSS, and R

# Warning: No AR1 residual with Mplus ML

- Mplus v.8 was developed with special features for the analysis of intensive longitudinal data
- These special features (e.g., autoregressive effects, AR1 residual) dramatically increase model complexity and likelihood of model nonconvergence when using ML estimation
- Mplus v.8 uses special syntax as well as Bayesian estimation to make estimation of these more complex models tractable
- Estimation of AR1 residual structure will be introduced in a later chapter of this workshop



# Intimacy Tx Example in Mplus

```
TITLE:    AILD Ch. 2 Time Course example (Intimacy Tx);
DATA:     FILE IS timecourse.dat;
VARIABLE: NAMES ARE id time time01 intimacy treatment;
          USEVAR ARE intimacy treatment time01;
          WITHIN =  time01;
          BETWEEN = treatment;
          CLUSTER = id;
ANALYSIS: TYPE = twolevel random;
          ESTIMATOR=ml;
MODEL:    %WITHIN%
          slope | intimacy on time01;
          %BETWEEN%
          intimacy slope on treatment;
          intimacy with slope;
OUTPUT:   sampstat cinterval;
```

timecourse.inp

# Comparing Results: SPSS and Mplus

SPSS MIXED:

**Estimates of Fixed Effects[a]**

| Parameter | Estimate | Std. Error | df | t | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|
| Intercept | 2.898974 | .202848 | 50 | 14.291 | .000 | 2.491542 | 3.306405 |
| time01 | .735203 | .340184 | 50 | 2.161 | .035 | .051923 | 1.418483 |
| treatment | -.056441 | .286870 | 50 | -.197 | .845 | -.632636 | .519754 |
| time01 * treatment | .921432 | .481093 | 50 | 1.915 | .061 | -.044871 | 1.887736 |

a. Dependent Variable: Intimacy outcome.

**Estimates of Covariance Parameters[a]**

| Parameter | | Estimate | Std. Error | Wald Z | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|
| Repeated Measures | Variance | 1.692497 | .090468 | 18.708 | .000 | 1.524155 | 1.879431 |
| Intercept + time01 [subject = id] | UN (1,1) | .642890 | .206767 | 3.109 | .002 | .342273 | 1.207538 |
| | UN (2,1) | -.473059 | .285942 | -1.654 | .098 | -1.033496 | .087378 |
| | UN (2,2) | 1.773096 | .581715 | 3.048 | .002 | .932118 | 3.372821 |

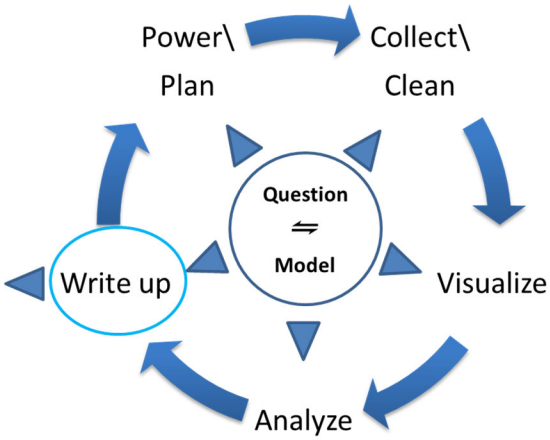
a. Dependent Variable: Intimacy outcome.

MPLUS:

```
MODEL RESULTS

                    Estimate       S.E.  Est./S.E.    Two-Tailed
                                                        P-Value

Within Level

 Residual Variances
    INTIMACY           1.693      0.091     18.701      0.000

Between Level

 SLOPE      ON
    TREATMENT          0.921      0.479      1.921      0.055

 INTIMACY   ON
    TREATMENT         -0.056      0.286     -0.196      0.844

 INTIMACY WITH
    SLOPE             -0.462      0.282     -1.639      0.101

 Intercepts
    INTIMACY           2.899      0.202     14.335      0.000
    SLOPE              0.735      0.339      2.168      0.030

 Residual Variances
    INTIMACY           0.637      0.204      3.115      0.002
    SLOPE              1.752      0.573      3.055      0.002
```



# **Write Up** and Disseminate your Findings



# Example Write-up: Time Course



In summary, the major hypothesis to be tested is whether females in the treatment group showed greater increases in intimacy over time than did females in the control group.

## METHOD

### Participants

Fifty opposite-sex couples were randomized to treatment ($n$ = 25) and control ($n$ = 25) conditions. The mean age of male partners was 32.4 years ($SD$ = 4.6). The mean age of female partners was 30.8 years ($SD$ = 3.4). All couples were homogeneous in terms of race. The racial breakdown in order of size was white ($n$ = 32, 64%), Asian ($n$ = 8, 16%), Hispanic ($n$ = 6, 12%), and black ($n$ = 4, 8%). Although couples were recruited into the study, in this paper we focus on the data for the female partners only.

### Measures

*Intimacy (female).* The six-item Reis and Shaver Intimacy Scale was used (Reis & Shaver, 1988). Raw scores were rescaled to a 0–10 interval, such that 0 was the lowest possible score and 10 was the highest possible score. Summary statistics for wives' intimacy over couples and time were: $M$ = 3.5, $SD$ = 1.6, range = 0–10.

*Time.* The 16 weeks of 1-hour therapy sessions were scaled such that 0 was the value for week 1 and 1 was the value for week 16, with the intervening 14 weeks spaced equally across the 0 to 1 interval. This scaling of time implies that a linear slope for time estimates the total change in intimacy over the complete therapeutic period.



### Procedure

Heterosexual couples were recruited from a marital therapy clinic in a large Midwestern city. The standard therapy for distressed couples was a 1-hour session each week for 16 consecutive weeks. Couples seeking treatment were randomly assigned to a treatment group that received therapy immediately, or to a control group that remained on a waiting list over the same 16-week period. All couples completed web-based questionnaires once per week. In the case of the treatment group, the reports were obtained on the evening prior to the day of each therapy session. Analyses were conducted on data from wives only.

## RESULTS

### Descriptive Statistics

The analysis dataset consisted of 50 (couples) * 16 (weeks) = 800 observations. Inspection of person-by-person scatterplots indicated that the within-person change in intimacy over time was approximately linear. The plots did not reveal any outliers, and there were no missing data.

### Multilevel Model of Intimacy Change

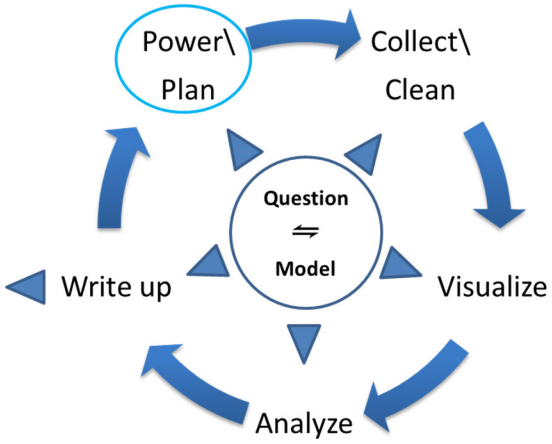
We specified and estimated a linear growth model for intimacy that allowed each wife to have her own initial level of intimacy and rate of change in intimacy. Because couples were randomized to treatment and control conditions, we hypothesized no group differences in average initial levels of intimacy. We predicted that both groups would show an increase in intimacy over the course of the study. Our key hypothesis was that wives in the treatment group would show a steeper rate of change in intimacy compared to those in the control group.

The results are presented in Table 1 and in Figures 1 and 2. Table

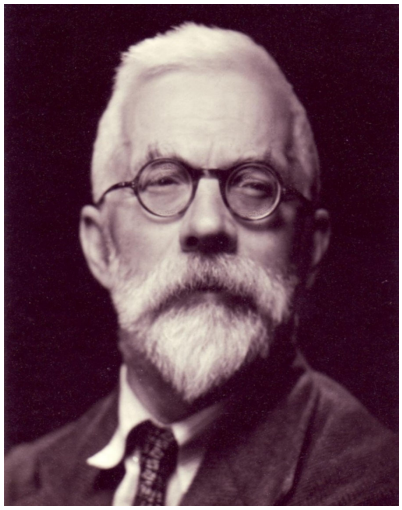
Write-up-Time-Course-Bolger-Laurenceau.pdf

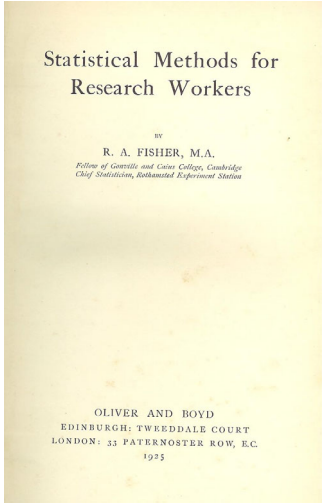


# Power/Plan a Future Replication



# In the Beginning was the Null Hypothesis





Statistical Methods for
Research Workers

BY

R. A. FISHER, M.A.

*Fellow of Gonville and Caius College, Cambridge*
*Chief Statistician, Rothamsted Experiment Station*

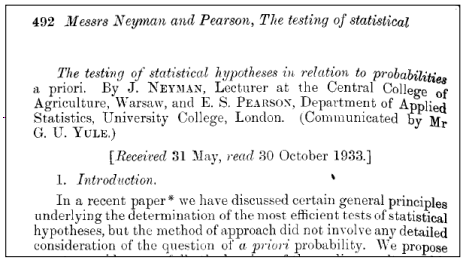
OLIVER AND BOYD
EDINBURGH: TWEEDDALE COURT
LONDON: 33 PATERNOSTER ROW, E.C.
1925



# Focusing on Type 1 Errors vs. Effect Size

- Fisher's Null Hypothesis testing framework was designed to prevent Type I errors
- Because his framework does not consider any specific alternative hypotheses it does not have the concept of effect size

# Neyman & Pearson



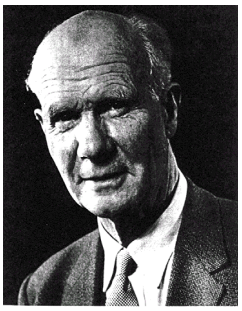
492 *Messrs Neyman and Pearson, The testing of statistical*

*The testing of statistical hypotheses in relation to probabilities a priori.* By J. NEYMAN, Lecturer at the Central College of Agriculture, Warsaw, and E. S. PEARSON, Department of Applied Statistics, University College, London. (Communicated by Mr G. U. YULE.)

[*Received* 31 May, *read* 30 October 1933.]

1. *Introduction.*

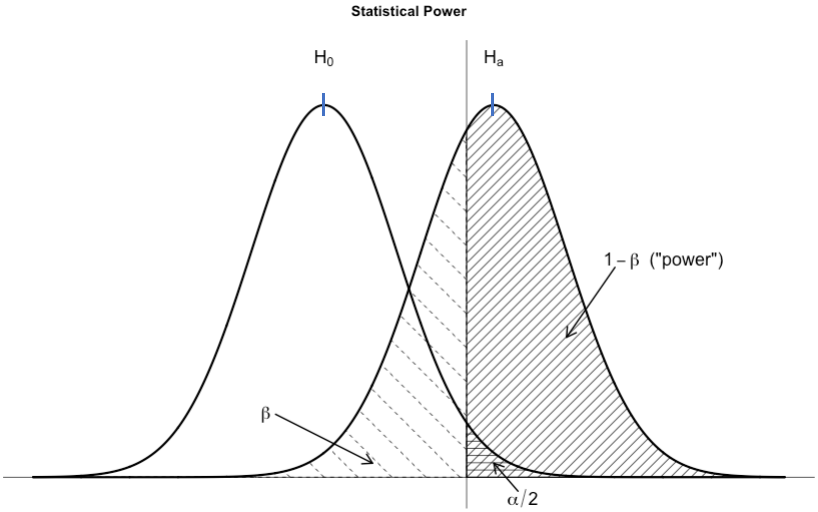
In a recent paper* we have discussed certain general principles underlying the determination of the most efficient tests of statistical hypotheses, but the method of approach did not involve any detailed consideration of the question of *a priori* probability. We propose



EGON SHARPE PEARSON



# Statistical Power: Two States of Affairs



## General Power Formula

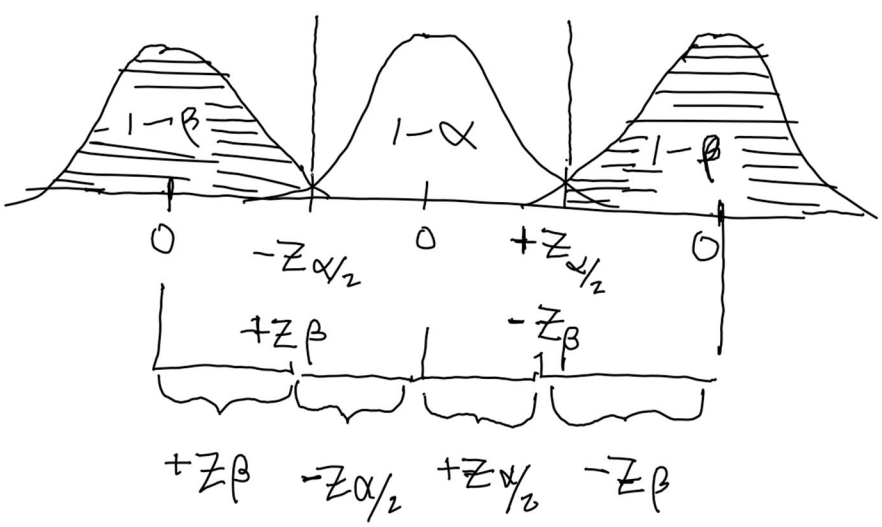
$$\frac{\hat{\delta}}{SE_{\hat{\delta}}} = z_{\frac{\alpha}{2}} - z_{\beta}$$

$$z_{\beta} = z_{\frac{\alpha}{2}} - \frac{\hat{\delta}}{SE_{\hat{\delta}}}$$

$$Power = (1 - Pr(z_{\beta}))$$



## Power Formula in a Picture




$$\frac{\hat{\delta}}{SE_{\hat{\delta}}} = z_{\frac{\alpha}{2}} - z_{\beta}$$

## Power Formula for Slopes in Linear Models

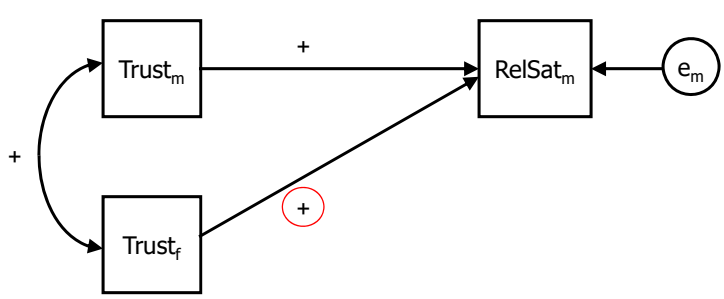
$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

$$\frac{\hat{\beta}_1}{\sqrt{\frac{\sigma_\varepsilon^2}{N\sigma_X^2}}} = z_{\frac{\alpha}{2}} - z_\beta$$

$$Power = (1 - Pr(z_\beta))$$



## Linear Regression Example



# Mplus Syntax for Regression Example

```
TITLE:    Cross-sectional Regression Model;
DATA:     FILE = relsat.txt; !Note that can also include path to data
VARIABLE:  NAMES = mrelsat1 frelsat1 mrelsat2 frelsat2 mtrust1 ftrust1;
          USEVAR = mrelsat1 mtrust1 ftrust1;
DEFINE:   CENTER mtrust1 ftrust1 (GRANDMEAN);
ANALYSIS:  TYPE = GENERAL;
MODEL:    mrelsat1 ON mtrust1 ftrust1;
OUTPUT:   SAMPSTAT CINTERVAL STDYX;
PLOT:     TYPE=PLOT1; !For basic histograms and scatterplots

!Exclamation point indicates a comment
```

relsatmplus.inp

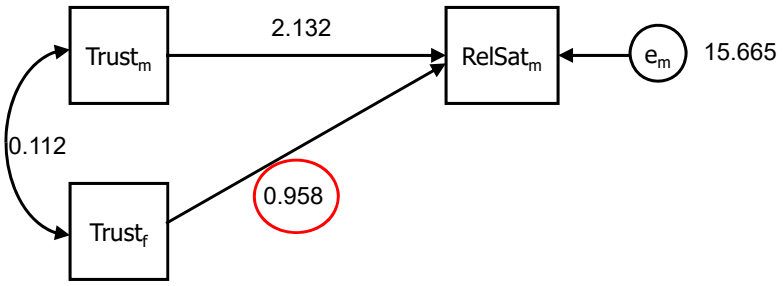


# relsatmplus.out

MODEL RESULTS

| | Estimate | S.E. | Est./S.E. | Two-Tailed P-Value |
|---|---|---|---|---|
| MRELSAT1 ON | | | | |
| MTRUST1 | 2.132 | 0.544 | 3.921 | 0.000 |
| FTRUST1 | 0.958 | 0.560 | 1.710 | 0.087 |
| Intercepts | | | | |
| MRELSAT1 | 30.852 | 0.417 | 73.951 | 0.000 |
| Residual Variances | | | | |
| MRELSAT1 | 15.664 | 2.335 | 6.708 | 0.000 |

# Regression Example: Unstandardized Estimates






# Power Monte Carlo Simulation

```
MONTECARLO:
        NAMES ARE mrelsat1 mtrust1 ftrust1;
        NOBSERVATIONS = 90;
        SEED = 5859;
        NREPS = 1000;
ANALYSIS:
        MODEL POPULATION:
        mrelsat1 ON mtrust1*2.132;
        mrelsat1 ON ftrust1*0.958;
        ftrust1 WITH mtrust1*0.112;
        [ mrelsat1*30.852 ];
        [ mtrust1*0 ];
        [ ftrust1*0 ];
        mrelsat1*15.664;
        mtrust1*0.610;
        ftrust1*0.575;
MODEL:
        mrelsat1 ON mtrust1*2.132;
        mrelsat1 ON ftrust1*0.958;
        ftrust1 WITH mtrust1*0.112;
        [ mrelsat1*30.852 ];
        [ mtrust1*0 ];
        [ ftrust1*0 ];
        mrelsat1*15.664;
        mtrust1*0.610;
        ftrust1*0.575;
OUTPUT: SAMPSTAT;
```

Note: Means and variances of predictors come from sample descriptive statistics.

MCrelsatmplus.inp

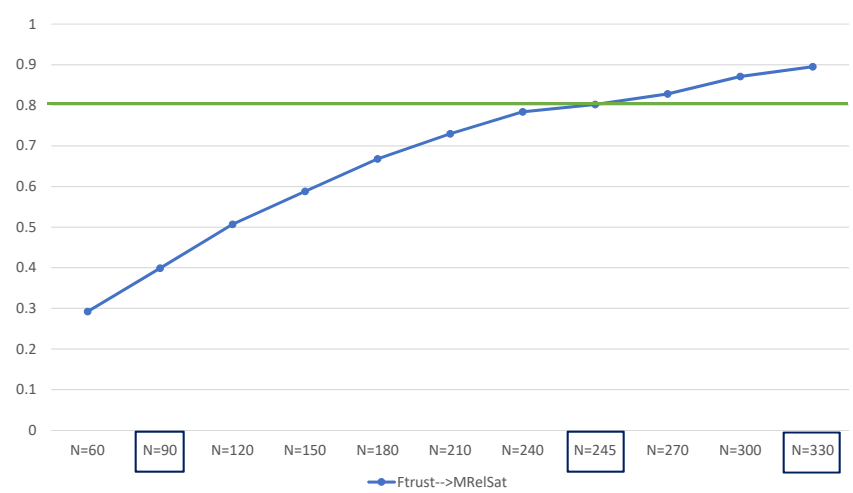
# MC Simulation Results

MODEL RESULTS

| | Population | ESTIMATES Average | Std. Dev. | S. E. Average | M. S. E. | 95% Cover | % Sig Coeff (Post-hoc power) |
|---|---|---|---|---|---|---|---|
| MRELSAT1 ON | | | | | | | |
| MTRUST1 | 2.132 | 2.1534 | 0.5333 | 0.5459 | 0.2846 | 0.944 | 0.977 |
| FTRUST1 | 0.958 | 0.9220 | 0.5857 | 0.5597 | 0.3440 | 0.937 | 0.386 |
| FTRUST1 WITH | | | | | | | |
| MTRUST1 | 0.112 | 0.1119 | 0.0632 | 0.0629 | 0.0040 | 0.946 | 0.427 |
| Means | | | | | | | |
| MTRUST1 | 0.000 | 0.0045 | 0.0860 | 0.0815 | 0.0074 | 0.931 | 0.069 |
| FTRUST1 | 0.000 | -0.0009 | 0.0837 | 0.0795 | 0.0070 | 0.933 | 0.067 |
| Intercepts | | | | | | | |
| MRELSAT1 | 30.852 | 30.8393 | 0.4004 | 0.4146 | 0.1603 | 0.953 | 1.000 |
| Variances | | | | | | | |
| MTRUST1 | 0.610 | 0.6008 | 0.0878 | 0.0896 | 0.0078 | 0.935 | 1.000 |
| FTRUST1 | 0.575 | 0.5715 | 0.0830 | 0.0852 | 0.0069 | 0.940 | 1.000 |
| Residual Variances | | | | | | | |
| MRELSAT1 | 15.664 | 15.1783 | 2.3107 | 2.2627 | 5.5699 | 0.901 | 1.000 |



# Power Curve for RelSat Regression Example



# Formula for Mixed Model

Formula for Mixed Model:

$$Y_{ij} = \gamma_{00} + \gamma_{01} W_j + \gamma_{10} T_{ij} + \gamma_{11} W_j T_{ij} + u_{0j} + u_{1j} T_{ij} + \varepsilon_{ij}$$

Covariance Matrix of Random Effects:

$$Var \begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} = \begin{bmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{bmatrix} = \mathrm{T}au$$



# Sampling Variance of Cross-Level Interaction

Sampling Variance of $\hat{\gamma}_{11}$: $\sigma^2_{\hat{\gamma}_{11}}$

Within Component

$$\sigma^2_{\hat{\gamma}_{11}} = \frac{\sigma^2_{\varepsilon}}{NT\sigma^2_{T_{ij}}} + \frac{\tau_{11}}{N}$$

Between Component

# Formula for Mixed Model

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \gamma_{11}W_jT_{ij} + u_{0j} + u_{1j}T_{ij} + \varepsilon_{ij}$$

$$\boxed{\sigma^2_{\hat{\gamma}_{11}} = \frac{\sigma^2_{\varepsilon}}{NT\sigma^2_{T_{ij}}} + \frac{\tau_{11}}{N}}$$

$$\frac{\hat{\gamma}_{11}}{\sqrt{\sigma^2_{\hat{\gamma}_{11}}}} = z_{\frac{\alpha}{2}} - z_{\beta}$$

$$Power = (1 - Pr(z_{\beta}))$$



# SPSS MIXED RESULTS:

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}T_{ij} + \boxed{\gamma_{11}W_jT_{ij}} + u_{0j} + u_{1j}T_{ij} + \varepsilon_{ij}$$

**Estimates of Fixed Effects[a]**

| Parameter | Estimate | Std. Error | df | t | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| Intercept ($\hat{\gamma}_{00}$) | 2.898974 | .207030 | 47.975 | 14.003 | .000 | 2.482707 | 3.315242 |
| time01 ($\hat{\gamma}_{10}$) | .735201 | .347199 | 47.998 | 2.118 | .039 | .037111 | 1.433292 |
| Treatment ($\hat{\gamma}_{01}$) | -.056442 | .292[illegible]5 | 47.975 | -.193 | .8[illegible] | -.645134 | .532249 |
| time01*treatment ($\hat{\gamma}_{11}$) | .921436 | .491013 | 47.998 | 1.877 | .067 | -.065813 | 1.908686 |

**Estimates of Covariance Parameters[a]**

| Parameter | | Estimate | Std. Error | Wald Z | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| Repeated Measures | AR1 diagonal ($\hat{\sigma}^2$) | 1.692482 | .092127 | 18.371 | .000 | 1.521216 | 1.883031 |
| | AR1 rho ($\hat{\rho}$) | -.000034 | .042175 | -.001 | .999 | -.082507 | .082439 |
| Intercept + time01 [subject = id] | UN (1,1) ($\hat{\tau}_{00}$) | .685773 | .221288 | 3.099 | .002 | .364344 | 1.290771 |
| | UN (2,1) ($\hat{\tau}_{01}$) | -.516135 | .306251 | -1.685 | .092 | -1.116375 | .084105 |
| | UN (2,2) ($\hat{\tau}_{11}$) | 1.893711 | .623774 | 3.036 | .002 | .992966 | 3.611547 |

# Power for Time Course Model: Mplus Syntax

```
MONTECARLO:
        NAMES ARE time intimacy treatment;
        NOBSERVATIONS = 800; NCSIZES = 1; CSIZES = 50 (16);
        SEED = 5859; NREPS = 1000;
        WITHIN = time; BETWEEN = treatment;
ANALYSIS:
        TYPE = twolevel random;
        MODEL POPULATION:
        %WITHIN%
        slope | intimacy ON time;
        [time*0.500];
        intimacy*1.693; time*0.094;
        %BETWEEN%
        slope ON treatment*0.921;
        intimacy ON treatment*-0.056;
        intimacy WITH slope*-0.516;
        [treatment*0.500]; [intimacy*2.899]; [slope*0.735];
        treatment*0.250; intimacy*0.687; slope*1.894;
MODEL:
        %WITHIN%
        slope | intimacy ON time;
        [time*0.500];
        intimacy*1.693; time*0.094;
        %BETWEEN%
        slope ON treatment*0.921;
        intimacy ON treatment*-0.056;
        intimacy WITH slope*-0.516;
        [treatment*0.500]; [intimacy*2.899]; [slope*0.735];
        treatment*0.250; intimacy*0.687; slope*1.894;
OUTPUT: SAMPSTAT TECH9;
```

Note: Means and variances of predictors come from sample descriptive statistics.

MCtimecourse.inp



**Translating SPSS Output to Mplus MC Input**

**Estim**

| Parameter | Estimate | Std. Error | lence Interval Upper Bound |
|---|---|---|---|
| Intercept | 2.898974 | .207030 | 3.315242 |
| time01 | .735201 | .347199 | 1.433292 |
| treatment | -.056442 | .292785 | .532249 |
| time01 * treatment | .921436 | .491013 | 1.908686 |

Dependent Variable: intimacy.

**Estimates of Covariance Paran**

| Parameter | | Estimate | Std. Error | und |
|---|---|---|---|---|
| Repeated Measures | AR1 diagonal | 1.692482 | .092127 | 031 |
| | AR1 rho | -3.418855E-5 | .042175 | 439 |
| Intercept + time01 [subject = id] | UN (1,1) | .685773 | .221288 | 771 |
| | UN (2,1) | -.516135 | .306251 | 105 |
| | UN (2,2) | 1.893711 | .623774 | 547 |

a. Dependent Variable: intimacy.

```
MONTECARLO:
        NAMES ARE time intimacy treatment;
        NOBSERVATIONS = 800;
        NCSIZES = 1;
        CSIZES = 50 (16);
        SEED = 5859;
        NREPS = 1000;
        WITHIN = time;
        BETWEEN = treatment;
ANALYSIS:
        TYPE = twolevel random;
        MODEL POPULATION:
        %WITHIN%
        slope | intimacy ON time;
        [time*0.500];
        intimacy*1.693;
        time*0.094;
        %BETWEEN%
        slope ON treatment*0.921;
        intimacy ON treatment*-0.056;
        intimacy WITH slope*-0.516;
        [treatment*0.500];
        [intimacy*2.899];
        [slope*0.735];
        treatment*0.250;
        intimacy*0.686;
        slope*1.894;
MODEL:
        %WITHIN%
        slope | intimacy ON time;
        [time*0.500];
        intimacy*1.693;
        time*0.094;
        %BETWEEN%
        slope ON treatment*0.921;
        intimacy ON treatment*-0.056;
        intimacy WITH slope*-0.516;
        [treatment*0.500];
        [intimacy*2.899];
        [slope*0.735];
        treatment*0.250;
        intimacy*0.686;
        slope*1.894;
OUTPUT: SAMPSTAT TECH9;
```

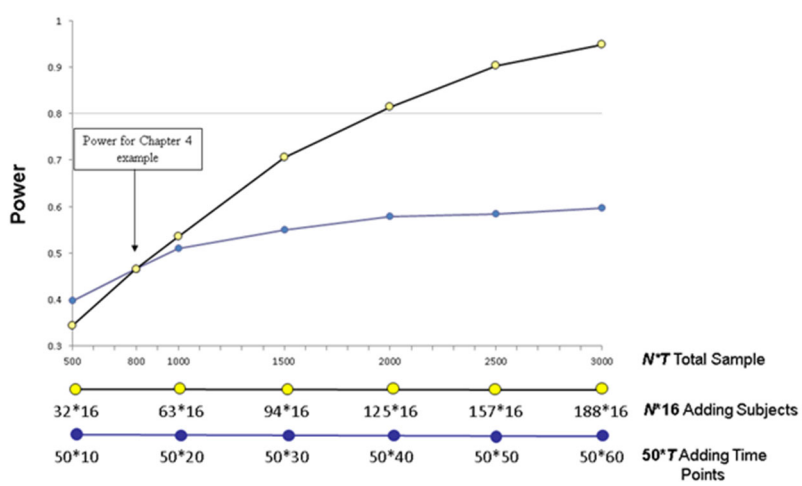
# Power Analysis Output in Mplus

MODEL RESULTS

| | Population | ESTIMATES Average | Std. Dev. | S. E. Average | M. S. E. | 95% Cover | % Sig Coeff (POWER) |
|---|---|---|---|---|---|---|---|
| **Within Level** | | | | | | | |
| Means | | | | | | | |
| TIME | 0.500 | 0.4999 | 0.0111 | 0.0107 | 0.0001 | 0.927 | 1.000 |
| Variances | | | | | | | |
| TIME | 0.094 | 0.0938 | 0.0046 | 0.0046 | 0.0000 | 0.937 | 1.000 |
| Residual Variances | | | | | | | |
| INTIMACY | 1.693 | 1.6952 | 0.0898 | 0.0888 | 0.0081 | 0.934 | 1.000 |
| **Between Level** | | | | | | | |
| SLOPE ON | | | | | | | |
| TREATMENT | 0.921 | 0.9111 | 0.5198 | 0.4959 | 0.2701 | 0.933 | 0.466 |
| INTIMACY ON | | | | | | | |
| TREATMENT | -0.056 | -0.0560 | 0.3098 | 0.2906 | 0.0959 | 0.914 | 0.088 |
| INTIMACY WITH | | | | | | | |
| SLOPE | -0.516 | -0.4724 | 0.2984 | 0.2888 | 0.0909 | 0.896 | 0.316 |
| Means | | | | | | | |
| TREATMENT | 0.500 | 0.5020 | 0.0722 | 0.0693 | 0.0052 | 0.938 | 1.000 |
| Intercepts | | | | | | | |
| INTIMACY | 2.899 | 2.8938 | 0.2239 | 0.2062 | 0.0501 | 0.920 | 1.000 |
| SLOPE | 0.735 | 0.7510 | 0.3659 | 0.3514 | 0.1340 | 0.937 | 0.558 |
| Variances | | | | | | | |
| TREATMENT | 0.250 | 0.2423 | 0.0491 | 0.0467 | 0.0025 | 0.911 | 1.000 |
| Residual Variances | | | | | | | |
| INTIMACY | 0.687 | 0.6358 | 0.2071 | 0.2055 | 0.0455 | 0.882 | 0.955 |
| SLOPE | 1.894 | 1.7977 | 0.5944 | 0.5882 | 0.3623 | 0.899 | 0.962 |



# Power Curves for Intimacy Treatment Example

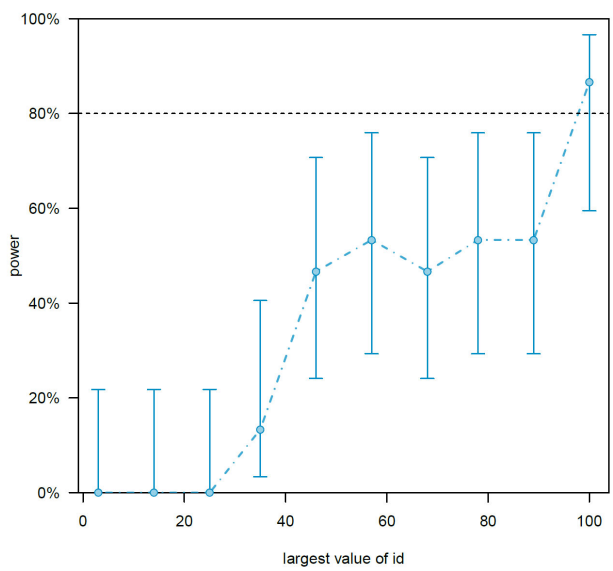


# Power for Time Course using *simr* in R

```
#################################################################
#Power analysis using simr
#################################################################

set.seed(111)
#Need to use lmer() instead of lme()
fit <- lmer(intimacy ~ time * treatment +
            (time | id), data = time)

#Use simr to estimate
pow0 <- powerSim(fit,
                 test = fixed("time01:treatment"),
                 nsim = 10)
pow0

fitsubj <- extend(fit, along="id", n=100)


powsubjcurve <- powerCurve(fitsubj,
                           test = fixed("time01:treatment"),
                           nsim = 20,
                           along = "id")
windows()
plot(powsubjcurve)

fittime <- extend(fit, along="time", n=50)
powtimecurve <- powerCurve(fittime,
                           test = fixed("time:treatment"),
                           nsim = 20,
                           along = "time")
plot(powtimecurve)

#################################################################
```



# Power Curve using *simr*



# Time Course with AR1 Residual in Mplus (Bayesian)

```
TITLE:    Extension of Time Course: Intimacy Treatment example;
DATA:     FILE IS timecourse.dat;
VARIABLE: NAMES ARE id time time01 intim tx; !Variable names shortened
          USEVAR ARE intim tx time01;
          WITHIN =  time01;
          BETWEEN = tx;
          CLUSTER = id;
          LAGGED = intim(1); !This is needed for lagging residual or outcome
ANALYSIS: TYPE = TWOLEVEL RANDOM;
          !ESTIMATOR=ml;
          ESTIMATOR = BAYES; !Needed for Mplus v.8 DSEM features
          PROCESSORS = 2; !Can make things run faster on multi-core systems
          BITERATIONS = (2000); !Facilitate stable convergence specifying a min # of iterations

MODEL:    %WITHIN%
          !sy | intimacy ON intimacy&1; !This is for a random autoregressive effect
          slope | intim on time01;
          !logv | intim; !This is for random level-1 residual variance
          intim^ on intim^1; !This is to specify AR(1) error structure
          !sar1|intim^ on intim^1; !This is for random AR(1) error structure
          %BETWEEN%
          intim slope on tx;
          intim with slope;
          [slope];

OUTPUT:   tech8; !Examine tech8 for PSR history
```

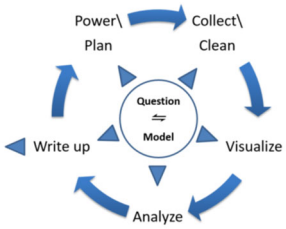
v8-timecourse-ar1-residual.inp



```
MODEL RESULTS

                                    Posterior  One-Tailed         95% C.I.
                      Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%  Significance

Within Level

 INTIM^     ON
    INTIM^1             0.003       0.044      0.471      -0.083       0.090

 Residual Variances
    INTIM               1.704       0.094      0.000       1.535       1.917      *

Between Level

 SLOPE      ON
    TX                  0.946       0.504      0.029      -0.041       1.904

 INTIM      ON
    TX                 -0.040       0.301      0.451      -0.670       0.521

 INTIM    WITH
    SLOPE              -0.580       0.376      0.016      -1.507      -0.049      *

 Intercepts
    INTIM               2.895       0.208      0.000       2.477       3.329      *
    SLOPE               0.735       0.352      0.023       0.010       1.417      *

 Residual Variances
    INTIM               0.762       0.275      0.000       0.381       1.464      *
    SLOPE               2.193       0.750      0.000       0.995       3.940      *
```

# Chapter Summary

- Full Cycle Approach to Modeling the Time Course (Continuous Outcome)
- Example Data Set and Syntax in SPSS, R, and Mplus for Visualization, Analysis, and Power
- Other syntax (e.g., HLM, SAS, Stata) for the Time Course example can be found at: www.intensivelongitudinal.com





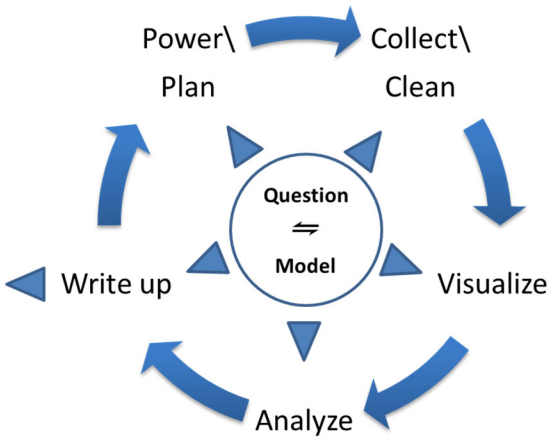

# Recommended Readings


- Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: A structural equation perspective*. Hoboken, NJ: Wiley.
- Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence.* New York: Oxford University Press.

# Chapter 3:

**Modeling the Within-Person Causal Process of Continuous Outcomes**

# Full Cycle Approach: Within-Person Process



## Process Example: Daily Conflict and Intimacy

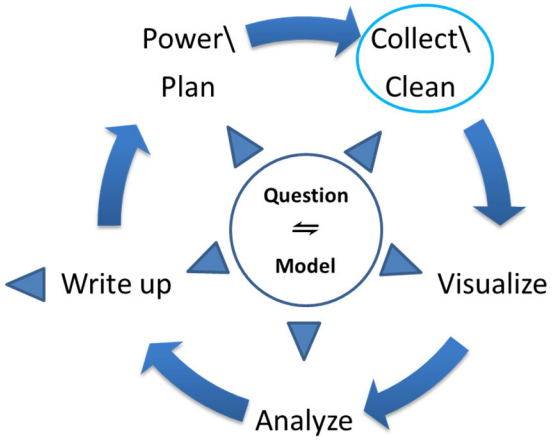
- Daily diary reports of arguments and relational intimacy by sixty-six women in a cohabiting intimate relationship
- Completed an on-line background set of global questionnaires and online nightly diaries for 28 consecutive evenings



## Process Example: Research Questions

- How much do daily conflicts lower intimacy for the typical person?
- How much do people differ in this relationship?
- Does relationship quality (RQ) buffer conflict reactivity such that those with higher RQ are less reactive to conflict?

## Collect your data/Clean your data






## Variables

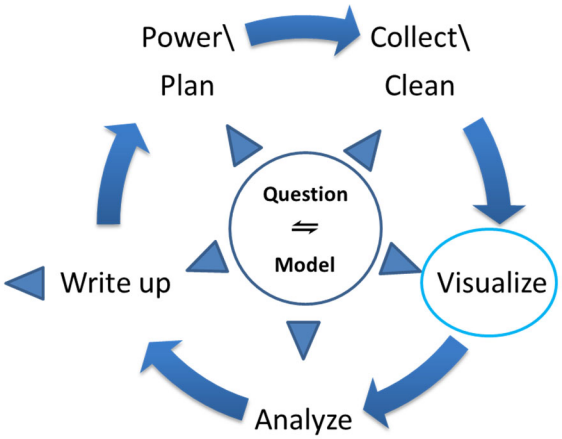
- id: Participant id
- time: Diary day (0, 1, 2, . . ., 27)
- time7c: Time in units of one week, centered
- intimacy: Daily intimacy score (0-10)
- conflict: Dichotomous daily predictor (0, 1)
- relqual: Relationship quality (0=low, 1=high RQ)

# A View of processdata.sav

| | id | time | time7c | intimacy | conflict | confb | confw | confbc | relqual |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | -1.93 | 4.78 | 0 | .107 | -.107 | -.114 | 1 |
| 2 | 1 | 1 | -1.79 | 2.07 | 0 | .107 | -.107 | -.114 | 1 |
| 3 | 1 | 2 | -1.64 | 3.80 | 0 | .107 | -.107 | -.114 | 1 |
| 4 | 1 | 3 | -1.50 | 3.69 | 0 | .107 | -.107 | -.114 | 1 |
| 5 | 1 | 4 | -1.36 | 4.65 | 0 | .107 | -.107 | -.114 | 1 |
| 6 | 1 | 5 | -1.21 | 3.61 | 0 | .107 | -.107 | -.114 | 1 |
| 7 | 1 | 6 | -1.07 | 3.78 | 0 | .107 | -.107 | -.114 | 1 |
| 8 | 1 | 7 | -.93 | 3.68 | 0 | .107 | -.107 | -.114 | 1 |
| 9 | 1 | 8 | -.79 | 6.47 | 0 | .107 | -.107 | -.114 | 1 |
| 10 | 1 | 9 | -.64 | 6.19 | 0 | .107 | -.107 | -.114 | 1 |
| 11 | 1 | 10 | -.50 | 4.16 | 1 | .107 | .893 | -.114 | 1 |
| 12 | 1 | 11 | -.36 | 1.50 | 0 | .107 | -.107 | -.114 | 1 |
| 13 | 1 | 12 | -.21 | 6.34 | 0 | .107 | -.107 | -.114 | 1 |
| 14 | 1 | 13 | -.07 | 7.12 | 0 | .107 | -.107 | -.114 | 1 |
| 15 | 1 | 14 | .07 | 5.43 | 0 | .107 | -.107 | -.114 | 1 |
| 16 | 1 | 15 | .21 | 5.44 | 1 | .107 | .893 | -.114 | 1 |
| 17 | 1 | 16 | .36 | 5.98 | 0 | .107 | -.107 | -.114 | 1 |
| 18 | 1 | 17 | .50 | 7.87 | 0 | .107 | -.107 | -.114 | 1 |
| 19 | 1 | 18 | .64 | 5.95 | 0 | .107 | -.107 | -.114 | 1 |
| 20 | 1 | 19 | .79 | 3.77 | 0 | .107 | -.107 | -.114 | 1 |
| 21 | 1 | 20 | .93 | 8.50 | 0 | .107 | -.107 | -.114 | 1 |
| 22 | 1 | 21 | 1.07 | 6.78 | 0 | .107 | -.107 | -.114 | 1 |
| 23 | 1 | 22 | 1.21 | 5.66 | 0 | .107 | -.107 | -.114 | 1 |
| 24 | 1 | 23 | 1.36 | 3.50 | 0 | .107 | -.107 | -.114 | 1 |
| 25 | 1 | 24 | 1.50 | 7.58 | 0 | .107 | -.107 | -.114 | 1 |
| 26 | 1 | 25 | 1.64 | 5.18 | 1 | .107 | .893 | -.114 | 1 |
| 27 | 1 | 26 | 1.79 | 6.16 | 0 | .107 | -.107 | -.114 | 1 |
| 28 | 1 | 27 | 1.93 | 2.68 | 0 | .107 | -.107 | -.114 | 1 |
| 29 | 2 | 0 | -1.93 | 7.64 | 0 | .107 | -.107 | -.114 | 1 |
| 30 | 2 | 1 | -1.79 | 8.12 | 0 | .107 | -.107 | -.114 | 1 |



# Visualize Your Data

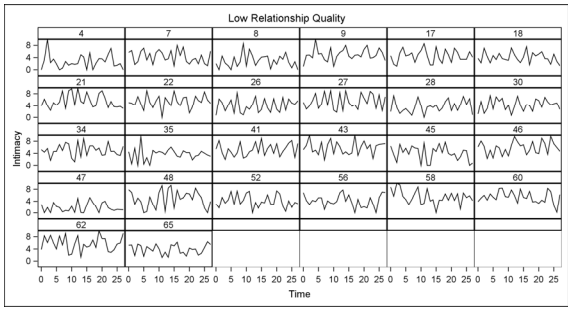


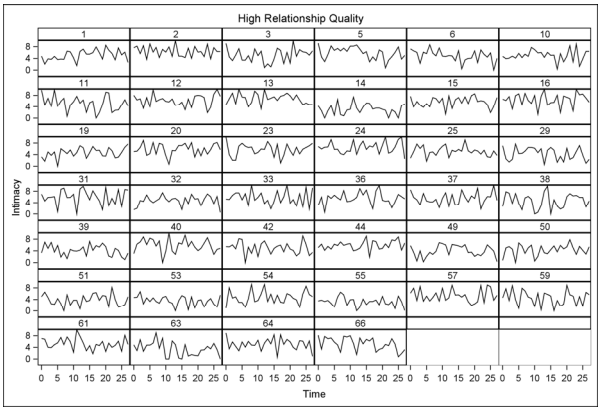
# Interim Comments

- Use this stage as an opportunity to detect errors
- Important variables such as Time and Daily Conflict will need to be transformed
- Although the underlying nature of Relationship Quality is best conceptualized as a dimension, we converted it to binary predictor in this example for didactic purposes
- Relationship Quality (the focal predictor) could have also been analyzed as a continuous predictor

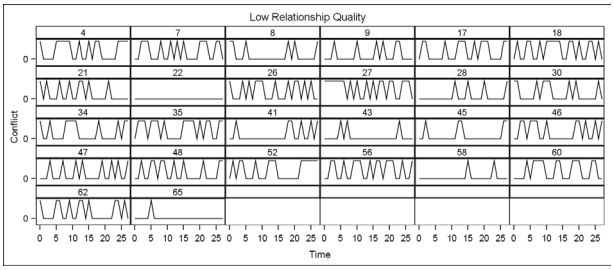


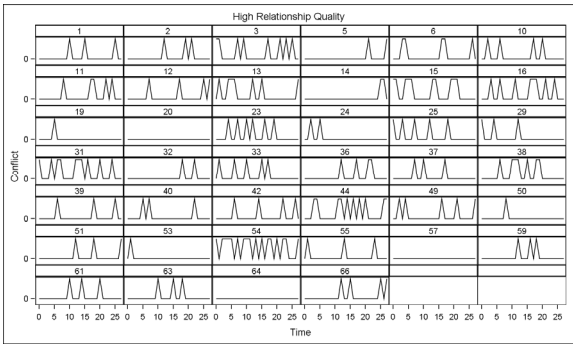
# Look at Time-Based Panel Plots: Outcome



# Look at Time-Based Panel Plots: Predictor



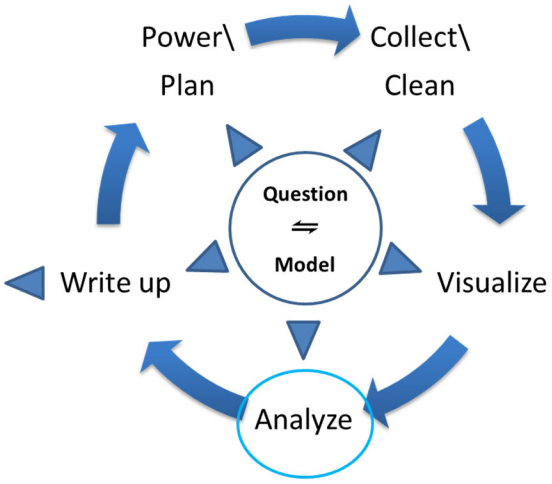






# Interim Comments

- In addition to basic detection of errors and monotonic time trends, panel plots give a sense of the amount of within-person variability in key outcomes and predictors

# Analyze Your Data






# Objectives

- The need to separate within- from between-person variability in time-varying predictors
- Calculating within-person and between-persons predictors
- Multilevel model for longitudinal data: multilevel and mixed model representations
- Interpreting and visualizing results
- Conducting analyses in SPSS, Mplus, and R

## Time-Varying Predictors: Within vs. Between

- Need to separate **within-person** and **between-person** effects of longitudinal predictors
- An individual's daily report of conflict fluctuates around his/her average number of conflicts and this average differs from person to person
- Multilevel models already handle separating within from between variability **in the outcome**



## Time-Varying Predictors: Within vs. Between

- **Daily intimacy (outcome)** has both within-person and between-person variability
- **Daily conflict (predictor)** *also* has both within-person and between-person variability
- Accounting for mean conflict allows for a **pure within-person interpretation** of the effect of daily conflict on daily intimacy

## Centering Level-1 Predictors

- To account for mean conflict, we will do **person-mean centering** of key time-varying predictors
- Person-means are the means across the scores on $X_{ij}$ for each individual, resulting in each person having their own mean on X (i.e., $X_{.j}$)
- These person-mean are then subtracted from the raw $X_{ij}$ scores
- This is not the typical form of centering from regression (i.e., subtracting a single constant); here we subtract a different constant for each person resulting in a version of $X_{ij}$ that only contains within-person variability



## Steps to calculate within and between conflict

- First, start with raw conflict (conflict)
- Second, calculate person-means of raw conflict (confb)
- Third, subtract person-means from raw conflict (confw)
- Fourth, take the person-means and center them (confbc)

# Centering Within- & Between-Person Conflict

1 Raw measure of conflict

2 Person-means of conflict

3 conflict – confb

4 Centered confb

processdata.sav

| | id | time | time7c | intimacy | conflict | confb | confw | confbc | relqual |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | -1.93 | 4.78 | 0 | .107 | -.107 | -.114 | 1 |
| 2 | 1 | 1 | -1.79 | 2.07 | 0 | .107 | -.107 | -.114 | 1 |
| 3 | 1 | 2 | -1.64 | 3.80 | 0 | .107 | -.107 | -.114 | 1 |
| 4 | 1 | 3 | -1.50 | 3.69 | 0 | .107 | -.107 | -.114 | 1 |
| 5 | 1 | 4 | -1.36 | 4.65 | 0 | .107 | -.107 | -.114 | 1 |
| 6 | 1 | 5 | -1.21 | 3.61 | 0 | .107 | -.107 | -.114 | 1 |
| 7 | 1 | 6 | -1.07 | 3.78 | 0 | .107 | -.107 | -.114 | 1 |
| 8 | 1 | 7 | -.93 | 3.68 | 0 | .107 | -.107 | -.114 | 1 |
| 9 | 1 | 8 | -.79 | 6.47 | 0 | .107 | -.107 | -.114 | 1 |
| 10 | 1 | 9 | -.64 | 6.19 | 0 | .107 | -.107 | -.114 | 1 |
| 11 | 1 | 10 | -.50 | 4.16 | 1 | .107 | .893 | -.114 | 1 |
| 12 | 1 | 11 | -.36 | 1.50 | 0 | .107 | -.107 | -.114 | 1 |
| 13 | 1 | 12 | -.21 | 6.34 | 0 | .107 | -.107 | -.114 | 1 |
| 14 | 1 | 13 | -.07 | 7.12 | 0 | .107 | -.107 | -.114 | 1 |
| 15 | 1 | 14 | .07 | 5.43 | 0 | .107 | -.107 | -.114 | 1 |
| 16 | 1 | 15 | .21 | 5.44 | 1 | .107 | .893 | -.114 | 1 |
| 17 | 1 | 16 | .36 | 5.98 | 0 | .107 | -.107 | -.114 | 1 |
| 18 | 1 | 17 | .50 | 7.87 | 0 | .107 | -.107 | -.114 | 1 |
| 19 | 1 | 18 | .64 | 5.95 | 0 | .107 | -.107 | -.114 | 1 |
| 20 | 1 | 19 | .79 | 3.77 | 0 | .107 | -.107 | -.114 | 1 |
| 21 | 1 | 20 | .93 | 8.50 | 0 | .107 | -.107 | -.114 | 1 |



# Centering Level-2 Predictors

- At level-2 , there are two options for centering Ws:
  - No centering of W
  - Centering W about its grand mean

# Causal Process Dataset

| | | $(T_{ij})$ | $(\breve{T}_{ij})$ | $(Y_{ij})$ | $(X_{ij})$ | $(X_{.j})$ | $(X_{ij}-X_{.j})$ | $(\breve{X}_{.j})$ | $(W_j)$ |
|---|---|---|---|---|---|---|---|---|---|
| | id | time | time7c | intimacy | conflict | confb | confw | confbc | relqual |
| 1 | 1 | 0 | -1.93 | 4.78 | 0 | .107 | -.107 | -.114 | 1 |
| 2 | 1 | 1 | -1.79 | 2.07 | 0 | .107 | -.107 | -.114 | 1 |
| 3 | 1 | 2 | -1.64 | 3.80 | 0 | .107 | -.107 | -.114 | 1 |
| 4 | 1 | 3 | -1.50 | 3.69 | 0 | .107 | -.107 | -.114 | 1 |
| 5 | 1 | 4 | -1.36 | 4.65 | 0 | .107 | -.107 | -.114 | 1 |
| 6 | 1 | 5 | -1.21 | 3.61 | 0 | .107 | -.107 | -.114 | 1 |
| 7 | 1 | 6 | -1.07 | 3.78 | 0 | .107 | -.107 | -.114 | 1 |
| 8 | 1 | 7 | -.93 | 3.68 | 0 | .107 | -.107 | -.114 | 1 |
| 9 | 1 | 8 | -.79 | 6.47 | 0 | .107 | -.107 | -.114 | 1 |
| 10 | 1 | 9 | -.64 | 6.19 | 0 | .107 | -.107 | -.114 | 1 |
| 11 | 1 | 10 | -.50 | 4.16 | 1 | .107 | .893 | -.114 | 1 |
| 12 | 1 | 11 | -.36 | 1.50 | 0 | .107 | -.107 | -.114 | 1 |
| 13 | 1 | 12 | -.21 | 6.34 | 0 | .107 | -.107 | -.114 | 1 |
| 14 | 1 | 13 | -.07 | 7.12 | 0 | .107 | -.107 | -.114 | 1 |
| 15 | 1 | 14 | .07 | 5.43 | 0 | .107 | -.107 | -.114 | 1 |
| 16 | 1 | 15 | .21 | 5.44 | 1 | .107 | .893 | -.114 | 1 |
| 17 | 1 | 16 | .36 | 5.98 | 0 | .107 | -.107 | -.114 | 1 |
| 18 | 1 | 17 | .50 | 7.87 | 0 | .107 | -.107 | -.114 | 1 |
| 19 | 1 | 18 | .64 | 5.95 | 0 | .107 | -.107 | -.114 | 1 |
| 20 | 1 | 19 | .79 | 3.77 | 0 | .107 | -.107 | -.114 | 1 |
| 21 | 1 | 20 | .93 | 8.50 | 0 | .107 | -.107 | -.114 | 1 |

$$\breve{T}_{ij} = (T_{ij} - T_{.j}) / 7$$

$$\breve{X}_{.j} = (X_{.j} - X_{..})$$



# Multilevel and Mixed Model Forms

**Level 1:**

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\breve{X}_{ij} - \breve{X}_{.j}) + \beta_{2j}\breve{T}_{ij} + \varepsilon_{ij}$$

**Level 2:**

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \gamma_{02}\breve{X}_{.j} + \gamma_{03}W_j\breve{X}_{.j} + u_{0j}$$

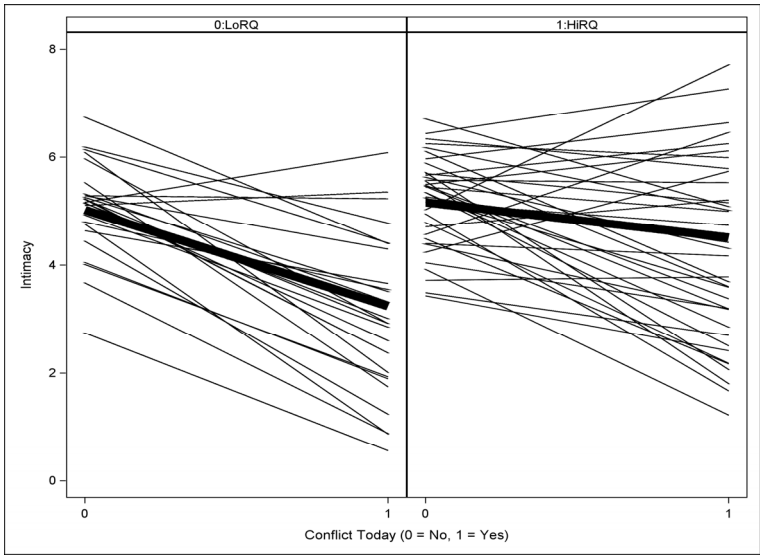
$$\beta_{1j} = \gamma_{10} + \gamma_{11}W_j + u_{1j}$$

$$\beta_{2j} = \gamma_{20}$$

**Mixed Model:**

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{02}\breve{X}_{.j} + \gamma_{03}W_j\breve{X}_{.j} + \gamma_{10}(\breve{X}_{ij} - \breve{X}_{.j}) + \gamma_{11}W_j(\breve{X}_{ij} - \breve{X}_{.j}) + \gamma_{20}\breve{T}_{ij} + u_{0j} + u_{1j}(\breve{X}_{ij} - \breve{X}_{.j}) + \varepsilon_{ij}$$

# Spaghetti Plot of Multilevel Modeling Results






# APA Formatted Table of Results

**TABLE 5.3. Estimates for Multilevel Model of Intimacy as a Function of Daily Conflict and Relationship Quality (This table has been duplicated as Table 1 of the example write-up.)**

| | Fixed effects (intercept, slopes) | Estimate | (*SE*) | $t^a$ | $p^b$ | $CI_{95}$ Lower | $CI_{95}$ Upper |
|---|---|---|---|---|---|---|---|
| $\gamma_{00}$ | Intercept | 4.53 | (0.22) | 20.48 | <.001 | 4.09 | 4.97 |
| $\gamma_{20}$ | Time (per 7 days) | –0.03 | (0.04) | –0.75 | .45 | –0.10 | 0.05 |
| $\gamma_{10}$ | Within conflict | –2.01 | (0.37) | –5.42 | <.001 | –2.75 | –1.27 |
| $\gamma_{01}$ | Relationship quality[c] | 0.65 | (0.28) | 2.29 | .025 | 0.83 | 1.21 |
| $\gamma_{11}$ | Within conflict by RQ | 1.02 | (0.49) | 2.06 | .044 | 0.03 | 2.00 |
| $\gamma_{02}$ | Between conflict | –0.84 | (1.10) | –0.76 | .45 | –3.05 | 1.49 |
| $\gamma_{03}$ | Between conflict by RQ | 2.53 | (1.68) | 1.50 | .14 | –0.83 | 5.89 |

| | Random effects ([co-]variances) | Estimate | (*SE*) | $z$ | $p$ | $CI_{95}$[d] Lower | $CI_{95}$[d] Upper |
|---|---|---|---|---|---|---|---|
| | Level 2 (between-person) | | | | | | |
| $\tau_{00}$ | Intercept | 0.81 | (0.17) | 4.87 | <.001 | 0.56 | 1.27 |
| $\tau_{11}$ | Within conflict | 2.71 | (0.67) | 4.07 | <.001 | 1.76 | 4.69 |
| $\tau_{10}$ | Intercept and within conflict | 0.40 | (0.24) | 1.65 | .098 | –0.07 | 0.88 |
| | Level 1 (within-person) | | | | | | |
| $\sigma^2_\varepsilon$ | Residual | 3.58 | (0.12) | 29.32 | <.001 | 3.35 | 3.83 |
| $\rho$ | Autocorrelation | –0.046 | (0.025) | –1.82 | .068 | –0.095 | 0.003 |

# SPSS Mixed Syntax

```
MIXED intimacy WITH relqual confbc confw time7c
  /FIXED=relqual confbc confbc*relqual confw
     confw*relqual time7c | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT confw | SUBJECT(id) COVTYPE(UN)
  /REPEATED=time7c | SUBJECT(id) COVTYPE(AR1).
```

Process-plots-and-mixed-spss-syntax.sps



# SPSS Model Results: Fixed Effects

**Estimates of Fixed Effects[a]**

| | Parameter | Estimate | Std. Error | df | t | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|---|
| $\gamma_{00}$ | Intercept | 4.532200 | .221262 | 63.092 | 20.483 | .000 | 4.090056 | 4.974344 |
| $\gamma_{01}$ | relqual | .647261 | .282056 | 63.077 | 2.295 | .025 | .083631 | 1.210891 |
| $\gamma_{02}$ | confbc | -.840931 | 1.103658 | 62.603 | -.762 | .449 | -3.046689 | 1.364827 |
| $\gamma_{03}$ | relqual * confbc | 2.527340 | 1.680882 | 62.461 | 1.504 | .138 | -.832202 | 5.886882 |
| $\gamma_{10}$ | confw | -2.010616 | .371079 | 52.144 | -5.418 | .000 | -2.755192 | -1.266040 |
| $\gamma_{11}$ | relqual * confw | 1.016407 | .492962 | 57.524 | 2.062 | .044 | .029462 | 2.003352 |
| $\gamma_{20}$ | time7c | -.027881 | .037071 | 649.216 | -.752 | .452 | -.100675 | .044913 |

a. Dependent Variable: intimacy.

# SPSS Model Results: Random Effects

**Estimates of Covariance Parameters[a]**

| Parameter | | | Estimate | Std. Error | Wald Z | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|---|
| Repeated Measures | AR1 diagonal | $\sigma_\varepsilon^2$ | 3.579187 | .122075 | 29.320 | .000 | 3.347746 | 3.826629 |
| | AR1 rho | $\rho$ | -.045757 | .025102 | -1.823 | .068 | -.094806 | .003513 |
| Intercept + confw [subject = id] | UN (1,1) | $\tau_{00}$ | .811845 | .166782 | 4.868 | .000 | .542757 | 1.214341 |
| | UN (2,1) | $\tau_{11}$ | .400675 | .242269 | 1.654 | .098 | -.074164 | .875514 |
| | UN (2,2) | $\tau_{10}$ | 2.711130 | .666437 | 4.068 | .000 | 1.674603 | 4.389234 |

a. Dependent Variable: intimacy.

**Random Effect Covariance Structure (G)[a]**

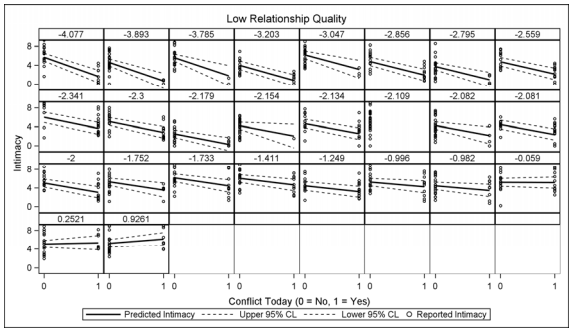
| | Intercept \| id | confw \| id |
|---|---|---|
| Intercept \| id | .811845 | .400675 |
| confw \| id | .400675 | 2.711130 |

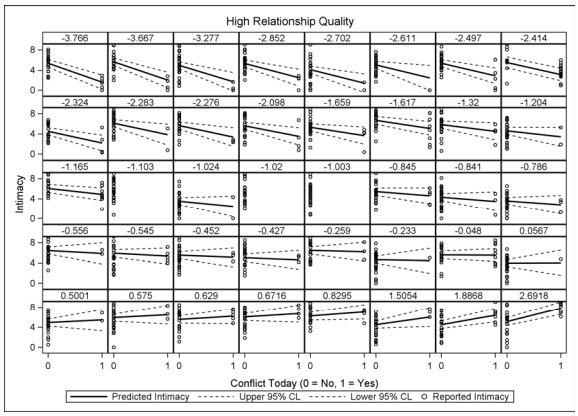
Unstructured

a. Dependent Variable: intimacy.

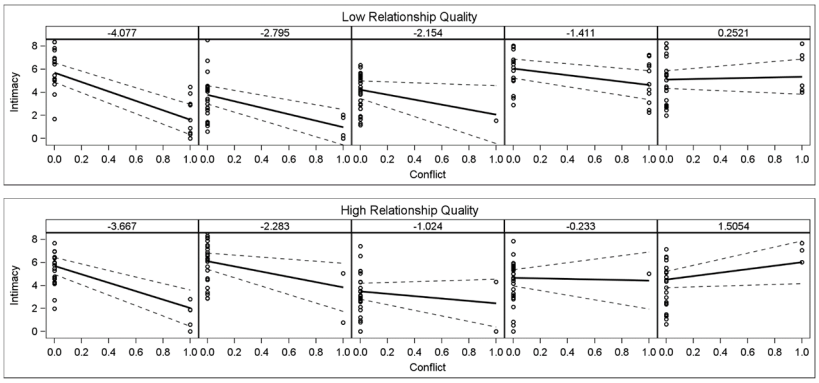


# Panel Plots with Predictions and Data



# Panel Plots with Predictions and Data




Plots of raw data and fitted lines representing effect of conflict on daily intimacy for five selected low (upper panel) and high (lower panel) global relationship women. The 95% confidence intervals for each slope are also shown.



# Reproducing Process Example in Mplus

```
TITLE:    Process example;
DATA:     FILE IS process.dat;
VARIABLE: NAMES ARE id conflict time time7c intimacy conflictb conflictw
                    relqual relqualrev;
          USEVAR ARE time7c intimacy conflictw conflictb relqual confbrq;
          WITHIN = conflictw time7c;
          BETWEEN = relqual conflictb confbrq;
          CLUSTER = id;
DEFINE:   confbrq=conflictb*relqual;
          CENTER conflictb (grandmean);
ANALYSIS: TYPE = TWOLEVEL RANDOM;
          ESTIMATOR=ml;
MODEL:    %WITHIN%
          confslp | intimacy on conflictw;
          intimacy on time7c;
          %BETWEEN%
          intimacy with confslp;
          intimacy on conflictb confbrq;
          intimacy confslp on relqual;
OUTPUT:   sampstat cinterval;
```

process.inp

# Reproducing Process Example in Mplus

SPSS MIXED:

**Estimates of Fixed Effects[a]**

| Parameter | Estimate | Std. Error | df | t | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|
| Intercept | 4.531919 | .214591 | 67.074 | 21.119 | .000 | 4.103603 | 4.960236 |
| relqual | .647465 | .273551 | 67.058 | 2.367 | .021 | .101463 | 1.193466 |
| confcb | -.840119 | 1.070214 | 66.643 | -.785 | .435 | -2.976487 | 1.296248 |
| relqual * confcb | 2.524121 | 1.629920 | 66.489 | 1.549 | .126 | -.729672 | 5.777914 |
| confcw | -2.022513 | .363853 | 53.883 | -5.559 | .000 | -2.752030 | -1.292995 |
| relqual * confcw | 1.032040 | .483764 | 59.607 | 2.133 | .037 | .064236 | 1.999844 |
| time7c | -.028433 | .038638 | 1750.599 | -.736 | .462 | -.104213 | .047348 |

a. Dependent Variable: intimacy.

**Estimates of Covariance Parameters[a]**

| Parameter | | Estimate | Std. Error | Wald Z | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|---|
| Repeated Measures | Variance | 3.588845 | .122354 | 29.332 | .000 | 3.356872 | 3.836849 |
| Intercept + confcw [subject = id] | UN (1,1) | .745592 | .152184 | 4.899 | .000 | .499760 | 1.112350 |
| | UN (2,1) | .383386 | .226771 | 1.691 | .091 | -.061077 | .827850 |
| | UN (2,2) | 2.577162 | .629880 | 4.092 | .000 | 1.596250 | 4.160853 |

a. Dependent Variable: intimacy.

Note. No AR(1) residual term

MPLUS:

```
MODEL RESULTS

                    Estimate       S.E.  Est./S.E.    Two-Tailed
                                                        P-Value
Within Level

 INTIMACY   ON
    TIME7C            -0.028      0.039     -0.737      0.461

 Residual Variances
    INTIMACY           3.589      0.122     29.329      0.000
Between Level

 CONFSLP    ON
    RELQUAL            1.032      0.483      2.138      0.033

 INTIMACY   ON
    CONFLICTB         -0.840      1.071     -0.784      0.433
    CONFBRQ            2.524      1.630      1.549      0.121
    RELQUAL            0.089      0.461      0.193      0.847

 INTIMACY WITH
    CONFSLP            0.385      0.226      1.702      0.089

 Intercepts
    INTIMACY           4.532      0.215     21.116      0.000
    CONFSLP           -2.022      0.363     -5.566      0.000

 Residual Variances
    INTIMACY           0.746      0.152      4.899      0.000
    CONFSLP            2.564      0.625      4.102      0.000
```



# Process Example with AR1 Residual in Mplus (Bayesian)

```
TITLE:    Extension of Process: Daily Conflict and Intimacy example with AR1 residual;
DATA:     FILE IS processdata.dat;
VARIABLE: NAMES ARE id conflict time time7c intimacy conflictb conflictw
                relqual relqualrev;
          USEVAR ARE time7c intimacy conflictw conflictb relqual confbrq;
          WITHIN = conflictw time7c;
          BETWEEN = relqual conflictb confbrq;
          CLUSTER = id;
          LAGGED = intimacy(1); !This is needed for lagging residual or outcome
DEFINE:   confbrq=conflictb*relqual;
          CENTER conflictb (grandmean);
ANALYSIS: TYPE = TWOLEVEL RANDOM;
          ESTIMATOR = BAYES;
          PROCESSORS = 2;
          BITERATIONS = (5000);
MODEL:    %WITHIN%
          confslp | intimacy on conflictw;
          intimacy^ on intimacy^1; !This is to specify AR(1) error structure
          intimacy on time7c;
          %BETWEEN%
          intimacy with confslp;
          intimacy on conflictb confbrq;
          intimacy confslp on relqual;
OUTPUT:   tech8 stdyx; !stdyx provides within standardization of confslp
```

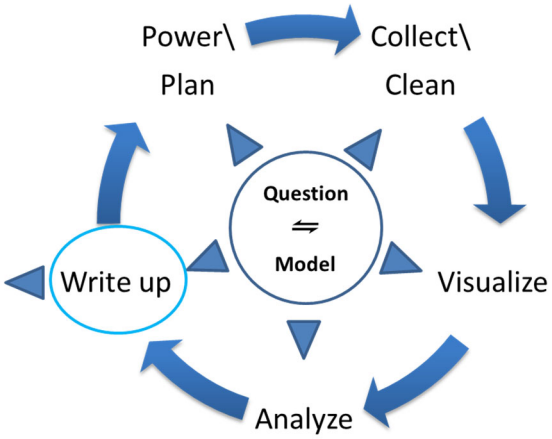
v8-process-ar1-residual.inp

| | Estimate | Posterior S.D. | One-Tailed P-Value | 95% C.I. Lower 2.5% | Upper 2.5% | Signif |
|---|---|---|---|---|---|---|
| **Within Level** | | | | | | |
| INTIMACY^ ON | | | | | | |
| INTIMACY^1 | -0.046 | 0.025 | 0.042 | -0.095 | 0.006 | |
| INTIMACY ON | | | | | | |
| TIME7C | -0.029 | 0.037 | 0.222 | -0.104 | 0.044 | |
| Residual Variances | | | | | | |
| INTIMACY | 3.579 | 0.125 | 0.000 | 3.347 | 3.836 | * |
| **Between Level** | | | | | | |
| CONFSLP ON | | | | | | |
| RELQUAL | 1.029 | 0.520 | 0.024 | 0.009 | 2.047 | * |
| INTIMACY ON | | | | | | |
| CONFLICTB | -0.815 | 1.143 | 0.241 | -2.999 | 1.445 | |
| CONFBRQ | 2.526 | 1.769 | 0.076 | -1.016 | 5.956 | |
| RELQUAL | 0.101 | 0.496 | 0.416 | -0.879 | 1.075 | |
| INTIMACY WITH | | | | | | |
| CONFSLP | 0.427 | 0.287 | 0.051 | -0.100 | 1.049 | |
| Intercepts | | | | | | |
| INTIMACY | 4.533 | 0.227 | 0.000 | 4.079 | 4.981 | * |
| CONFSLP | -2.024 | 0.392 | 0.000 | -2.771 | -1.234 | * |
| Residual Variances | | | | | | |
| INTIMACY | 0.892 | 0.200 | 0.000 | 0.599 | 1.369 | * |
| CONFSLP | 3.017 | 0.793 | 0.000 | 1.836 | 4.932 | * |

# Interim Comments

- Separating within- from between-person variability in time-varying predictors is a critical step
- It is useful to understand both the mixed and multilevel forms of the equation-based model(s)
- It's important to be able to visualize individual and group predictions from the model as a spaghetti plot and/or as individual panel plots with predictions superimposed on the data
- Findings reproduced across SPSS, Mplus, and R

# Write Up Your Findings






# Example APA Style Write-up: Process Example



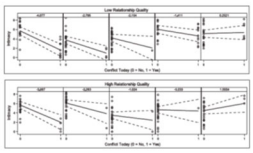


**FIGURE 5.6.** Intimacy as a function of daily conflict: Raw data and fitted regression lines for participants at the 5th, 25th, 50th, 75th, and 95th slope percentiles for the low- and high-relationship quality groups. Pairs of dashed lines show 95% confidence intervals. (This figure has been duplicated as Figure 2 of the example write-up.)

### The Write-Up

As in Chapter 4, we begin the write-up with a statement of the hypothesis to be tested, as it might appear at the end of an Introduction section of an APA-style empirical paper.

In sum, the key hypothesis to be tested is whether global relationship quality is a moderator of the impact of daily conflicts on intimacy.

**METHOD**

**Sample**

The sample consisted of 66 women in a cohabiting intimate relationship. Fifty-eight of these were in an opposite-sex relationship and eight were in a same-sex relationship. The women had a mean age of 26.2 years ($SD = 3.1$). The racial breakdown in order of size was white ($n = 38$, 58%), Asian ($n = 12$, 18%), Hispanic ($n = 8$, 12%), and black ($n = 8$, 12%).



**Measures**

*Daily conflict.* Conflict was measured each day by the following diary question: "Did you experience any tension or disagreement with your partner today?" A "No" answer was coded 0, and a "Yes" answer was coded 1. To facilitate interpretation of the intercept in the analyses, we grand-mean centered scores on this variable by subtracting the mean conflict across subjects and time points ($M = 0.22$) from each score. In addition, because conflict varied both between- and within-subjects and because we wished to focus on within-subjects variation, we created a between-subjects and within-subjects version of the variable, *between conflict* and *within conflict*, respectively.

*Daily intimacy.* The six-item Reis and Shaver Intimacy Scale was used (Reis & Shaver, 1988). Raw scores were rescaled to a 0–10 interval, such that 0 was the lowest possible score and 10 was the highest possible score. Summary statistics for intimacy over participants and time were $M = 4.8$, $SD = 2.3$, range = 0–10.

*Relationship quality.* Participants completed the single-item measure of how globally satisfied they felt about their relationship. The question was "Overall, how satisfied are you with your relationship with [intimate partner]?" The response options were (with $n$'s in parentheses): 5 = best I could ever imagine a relationship being ($n = 10$), 4 = extremely satisfied ($n = 18$), 3 = moderately satisfied ($n = 12$), 2 = a bit dissatisfied ($n = 19$), 1 = very dissatisfied ($n = 7$). A dichotomous (0, 1) version used in the analyses was created by combining codes 3, 4, and 5 into a high-RQ group ($n = 40$, 61%) and codes 1 and 2 into a low-RQ group ($n = 26$, 39%).

**Procedure**

Participants were recruited using flyers on a university campus. They responded to the flyers by e-mail or phone. Following recruitment, they

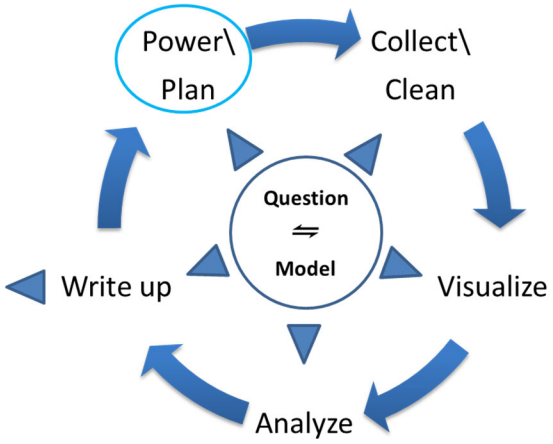
Write-up-Process-Bolger-Laurenceau.pdf

# Interim Comments

- The example write-up of the process data gives you an idea of what level of detail is necessary in communicating results
- The table of parameter estimates gives all the relevant numbers and only the substantively important ones need to be highlighted in the text
- We also show what graphs are essential, namely, the spaghetti plot and an example of data and predictions for individuals representing important positions in the distribution of effects in the sample



# Power/Plan a Replication Study



# Objectives

- The importance of conducting a power analysis when planning a future replication study or extension
- Conducting Monte Carlo power simulations in Mplus
- Comments on power analysis for process models



# Mplus Syntax: Monte Carlo Power Simulation

```
TITLE: Monte Carlo power simulation for process example;
MONTECARLO:
        NAMES ARE day7c intimacy confcw confcb relqual rqconfcb;
        NOBSERVATIONS = 1848;
        NCSIZES = 1;
        CSIZES = 66 (28);
        SEED = 5859;
        NREPS = 1000;
        WITHIN = day7c confcw;
        BETWEEN = confcb relqual rqconfcb;
ANALYSIS:
        TYPE = TWOLEVEL RANDOM;
        PROCESSORS = 4;
MODEL POPULATION:
        %WITHIN%
        slope | intimacy ON confcw;
        intimacy ON day7c*-0.028;
        intimacy*3.579;
        [confcw*0]; confcw*0.146;
        [day7c*0]; day7c*1.332
        %BETWEEN%
        slope ON relqual*1.016;
        intimacy ON confcb*-0.841;
        intimacy ON relqual*0.647;
        intimacy ON rqconfcb*2.527;
        intimacy WITH slope*0.401;
        [relqual*0.610]; relqual*0.239;
        [confcb*0]; confcb*0.027;
        [rqconfcb*-0.041]; rqconfcb*0.009;
        [intimacy*4.532]; intimacy*0.812;
        [slope*-2.011]; slope*2.711;
MODEL:
        %WITHIN%
        slope | intimacy ON confcw;
        intimacy ON day7c*-0.028;
        intimacy*3.579;
        %BETWEEN%
        slope ON relqual*1.016;
        intimacy ON confcb*-0.841;
        intimacy ON relqual*0.647;
        intimacy ON rqconfcb*2.527;
        intimacy WITH slope*0.401;
        [intimacy*4.532];
        [slope*-2.011];
        intimacy*0.812;
        slope*2.711;
OUTPUT:
```

Note: Means and variances of predictors come from sample descriptive statistics.

Mcprocessmplus.inp

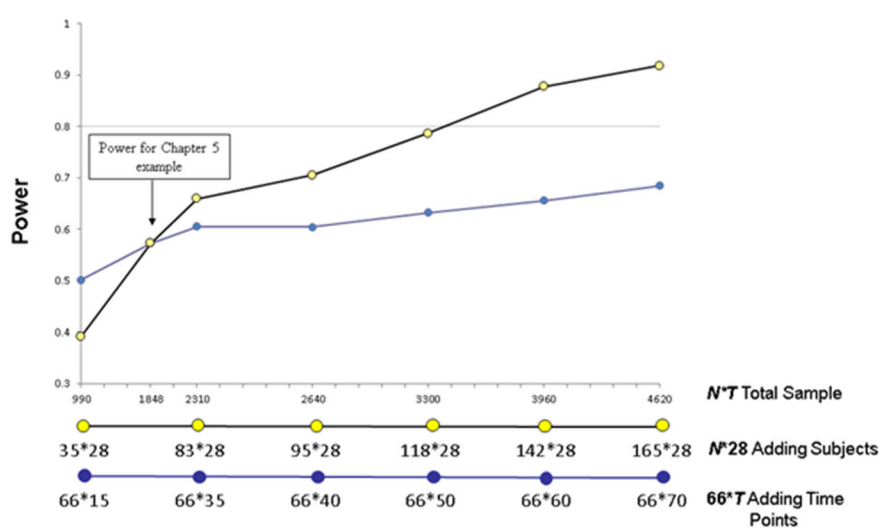
# Mplus Output: Monte Carlo Power Simulation

MODEL RESULTS

| | Population | ESTIMATES Average | Std. Dev. | S. E. Average | M. S. E. | 95% Cover | % Sig Coeff |
|---|---|---|---|---|---|---|---|
| Within Level | | | | | | | |
| INTIMACY ON | | | | | | | |
| DAY7C | -0.028 | 0.1121 | 4.5261 | 4.4316 | 20.4850 | 0.936 | 0.064 |
| Residual Variances | | | | | | | |
| INTIMACY | 3.579 | 3.5765 | 0.1215 | 0.1204 | 0.0148 | 0.947 | 1.000 |
| Between Level | | | | | | | |
| SLOPE ON | | | | | | | |
| RELQUAL | 1.016 | 1.0088 | 0.5273 | 0.4697 | 0.2778 | 0.915 | 0.573 |
| INTIMACY ON | | | | | | | |
| CONFCB | -0.841 | -0.8366 | 0.7536 | 0.6978 | 0.5673 | 0.917 | 0.265 |
| RELQUAL | 0.647 | 0.6537 | 0.2506 | 0.2399 | 0.0628 | 0.939 | 0.768 |
| RQCONFCB | 2.527 | 2.5575 | 1.3218 | 1.2100 | 1.7464 | 0.927 | 0.572 |
| INTIMACY WITH | | | | | | | |
| SLOPE | 0.401 | 0.3993 | 0.2385 | 0.2225 | 0.0568 | 0.927 | 0.432 |
| Intercepts | | | | | | | |
| INTIMACY | 4.532 | 4.5269 | 0.1981 | 0.1931 | 0.0392 | 0.939 | 1.000 |
| SLOPE | -2.011 | -1.9919 | 0.3996 | 0.3677 | 0.1599 | 0.926 | 0.999 |
| Residual Variances | | | | | | | |
| INTIMACY | 0.812 | 0.7612 | 0.1647 | 0.1510 | 0.0297 | 0.883 | 1.000 |
| SLOPE | 2.711 | 2.6127 | 0.6236 | 0.6014 | 0.3981 | 0.900 | 1.000 |



# Power Curves for Process Example



## Power/Plan a Replication: Concluding Comments

- Need (at least guesses for)
  - Effect sizes
  - Within & between variances
  - Within & between covariances
  - Number of participants & time points
- If you **do not** have informed guesses
  - Sensitivity analyses: Use range of values to see how large/small parameters need to be to have adequate power



## Power/Plan a Replication: Concluding Comments

- All other things being equal, more participants buys more power
  - Assuming you can reliably capture the process with the given number of time points
- Some events are rare, some processes take time to unfold
  - There will be some minimum number of time points that are necessary to detect an effect

## Power: Final Comments

- Echoing the previous chapter, assessing power for intensive longitudinal data is a complex undertaking
- Conducting an intensive longitudinal study is not for the faint of heart and can be a yeoman's undertaking; considering statistical power is important as a first step
- While understanding the logic of Monte Carlo simulation and its implementation in Mplus may require substantial effort for those not already familiar, the payoff can be large because it is an "all-purpose" approach to power flexible enough to accommodate a range of IL designs as well as other single and multilevel designs



## Power: Final Comments

- A take-home message on power for IL designs might be that, all other things being equal, you get more "bang for your buck" from adding participants compared to adding time points
- An important caveat to this take-home message is that there needs to be a sufficient number of time points to allow the events or experiences being assessed to unfold sufficiently

## Process Extension: Multiple Assessments per Day

- Handling unequal time intervals when examining lagged effects

## Objectives

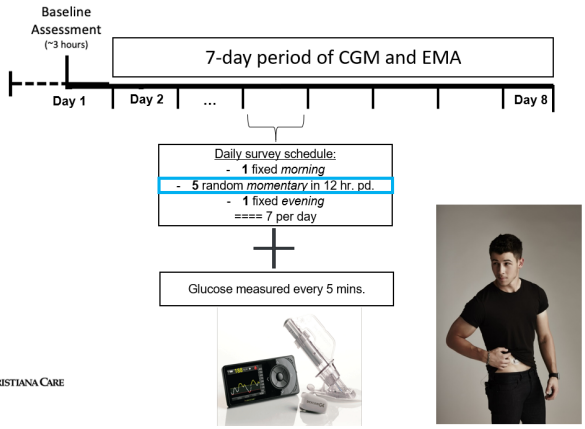
- Explain why estimating lagged effects of previous X on current Y produces biased effects in EMA/ESM designs where there are unequal time intervals between momentary assessments
- Describe an approach to handling this issue using DSEM in Mplus

# Visualization EMA Design

***Daily Diabetes Management in the Marital Context***

***National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK/NIH): R21DK098679***

**Approximate Timeline**

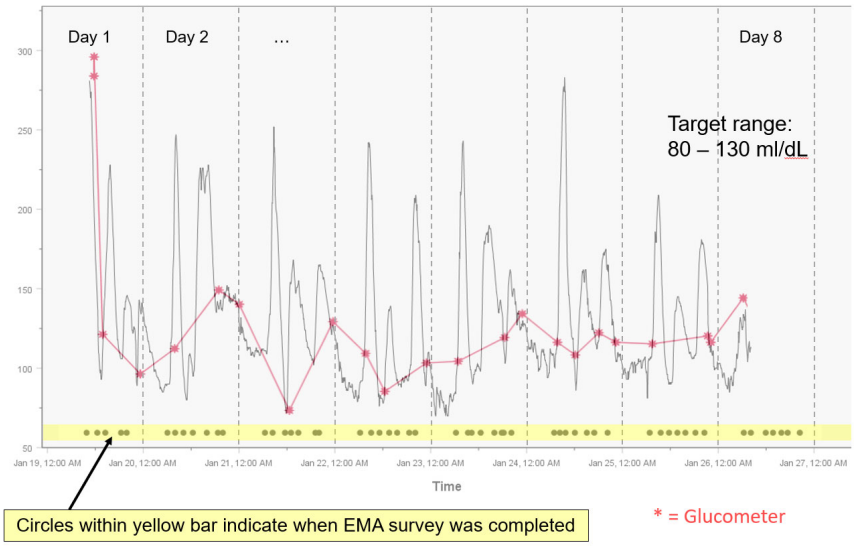



CHRISTIANA CARE

UNIVERSITY OF DELAWARE



# Example Raw Data for ID# 169



## Design Overview

- 63 patients (and partners/spouses)
- CGM every 5 minutes, 24 hours/day, 7 days
- EMAs 5X per day for 7 days
- Positive affect: 3 items from PANAS (e.g., “excited”, “interested”; Watson & Clark, 1999)
- Intimacy: “At this moment, how intimate/connected do you feel with your spouse/partner?”
- All on 0-4 Likert scale



## Mplus8 for EMA/ESM

- Time series based models assume equally-spaced intervals of time
- EMA/ESM produces unequal, subject-specific intervals
- Need to use TINTERVAL to create equally-spaced bins and drop EMAs into a particular bin and fill rest with missing values (avoid more than ~80% missing)
- Need an index of time that goes from first EMA to last EMA for each participant

# Dataset Before TINTERVAL

| ptID | Day | Hour | Index1hr | mmindex | pintim | ppa |
|---|---|---|---|---|---|---|
| 103 | 0 | 9 | 0 | 1 | -999 | -999.00 |
| 103 | 0 | 11 | 2 | 2 | 3 | 1.33 |
| 103 | 0 | 13 | 4 | 3 | 3 | 1.00 |
| 103 | 0 | 15 | 6 | 4 | 0 | 1.00 |
| 103 | 0 | 19 | 10 | 5 | -999 | -999.00 |
| 103 | 1 | 9 | 24 | 6 | 3 | 1.00 |
| 103 | 1 | 12 | 27 | 7 | 3 | 1.33 |
| 103 | 1 | 14 | 29 | 8 | 3 | 1.33 |
| 103 | 1 | 16 | 31 | 9 | 3 | 1.33 |
| 103 | 1 | 18 | 33 | 10 | 3 | 1.33 |
| 103 | 2 | 9 | 48 | 11 | 4 | 1.33 |
| 103 | 2 | 11 | 50 | 12 | 3 | 1.33 |
| 103 | 2 | 13 | 51 | 13 | 3 | 1.33 |
| 103 | 2 | 16 | 54 | 14 | 3 | 1.67 |
| 103 | 2 | 19 | 57 | 15 | 3 | 1.67 |
| 103 | 3 | 9 | 64 | 16 | 3 | 2.00 |
| 103 | 3 | 11 | 65 | 17 | 3 | 1.67 |
| 103 | 3 | 14 | 66 | 18 | 3 | 2.00 |
| 103 | 3 | 17 | 67 | 19 | 3 | 1.67 |
| 103 | 3 | 19 | 68 | 20 | 2 | .67 |
| 103 | 4 | 10 | 78 | 21 | 3 | 2.00 |
| 103 | 4 | 12 | 80 | 22 | 3 | 2.33 |
| 103 | 4 | 15 | 83 | 23 | -999 | -999.00 |
| 103 | 4 | 16 | 84 | 24 | 3 | 1.67 |
| 103 | 4 | 20 | 88 | 25 | 3 | 2.33 |
| 103 | 5 | 8 | 100 | 26 | 3 | .67 |
| 103 | 5 | 10 | 102 | 27 | 3 | 1.00 |
| 103 | 5 | 13 | 105 | 28 | 3 | 1.33 |
| 103 | 5 | 17 | 109 | 29 | 3 | 1.00 |
| 103 | 5 | 19 | 111 | 30 | 2 | 2.33 |



# Syntax for EMA Analysis with TINTERVAL

```
DATA:   FILE = EMA-pintim-ppa-1HR-nomiss-jpl.dat;
VARIABLE: NAMES = ptID Day Hour Index1hr mmindex pintim ppa;
    MISSING ARE ALL (-999);
    usevar =  pintim ppa;
    CLUSTER = ptid;
    LAGGED =  pintim (1) ppa (1);
    TINTERVAL = Index1hr (1);
DEFINE:
ANALYSIS:
    TYPE = TWOLEVEL RANDOM;
    ESTIMATOR = BAYES;
    PROCESSORS = 2;
    BITERATIONS = (5000);
MODEL:
    %WITHIN%
    s1|pintim on pintim&1;
    s2|pintim on ppa&1;
    s3|ppa on ppa&1;
    s4|ppa on pintim&1;
    %BETWEEN%
    pintim with ppa;
    pintim ppa s1 s2 s3 s4;
    pintim ppa s1 s2 s3 s4 with pintim ppa s1 s2 s3 s4;
OUTPUT: stand fscomparison;
PLOT: TYPE = PLOT3; FACTORS=ALL;
SAVEDATA:   FILE=EMA-pa-intim-tint.dat;
            MISSFLAG=-999;
```

# Before (Left) and After (Right) using TINTERVAL

| ptID | Day | Hour | Index1hr | mmindex | pintim | ppa |
|---|---|---|---|---|---|---|
| 103 | 0 | 9 | 0 | 1 | -999 | -999.00 |
| 103 | 0 | 11 | 2 | 2 | 3 | 1.33 |
| 103 | 0 | 13 | 4 | 3 | 3 | 1.00 |
| 103 | 0 | 15 | 6 | 4 | 0 | 1.00 |
| 103 | 0 | 19 | 10 | 5 | -999 | -999.00 |
| 103 | 1 | 9 | 24 | 6 | 3 | 1.00 |
| 103 | 1 | 12 | 27 | 7 | 3 | 1.33 |
| 103 | 1 | 14 | 29 | 8 | 3 | 1.33 |
| 103 | 1 | 16 | 31 | 9 | 3 | 1.33 |
| 103 | 1 | 18 | 33 | 10 | 3 | 1.33 |
| 103 | 2 | 9 | 48 | 11 | 4 | 1.33 |
| 103 | 2 | 11 | 50 | 12 | 3 | 1.33 |
| 103 | 2 | 13 | 51 | 13 | 3 | 1.33 |
| 103 | 2 | 16 | 54 | 14 | 3 | 1.67 |
| 103 | 2 | 19 | 57 | 15 | 3 | 1.67 |
| 103 | 3 | 9 | 64 | 16 | 3 | 2.00 |
| 103 | 3 | 11 | 65 | 17 | 3 | 1.67 |
| 103 | 3 | 14 | 66 | 18 | 3 | 2.00 |
| 103 | 3 | 17 | 67 | 19 | 3 | 1.67 |
| 103 | 3 | 19 | 68 | 20 | 2 | .67 |
| 103 | 4 | 10 | 78 | 21 | 3 | 2.00 |
| 103 | 4 | 12 | 80 | 22 | 3 | 2.33 |
| 103 | 4 | 15 | 83 | 23 | -999 | -999.00 |
| 103 | 4 | 16 | 84 | 24 | 3 | 1.67 |
| 103 | 4 | 20 | 88 | 25 | 3 | 2.33 |
| 103 | 5 | 8 | 100 | 26 | 3 | .67 |
| 103 | 5 | 10 | 102 | 27 | 3 | 1.00 |
| 103 | 5 | 13 | 105 | 28 | 3 | 1.33 |
| 103 | 5 | 17 | 109 | 29 | 3 | 1.00 |
| 103 | 5 | 19 | 111 | 30 | 2 | 2.33 |

| PTID | TIMEPOINT | PINTIM | PPA | PINTIMLG1 | PPALG1 |
|---|---|---|---|---|---|
| 103 | 1 | 3.000 | 1.333 | -999.000 | -999.000 |
| 103 | 2 | -999.000 | -999.000 | 3.000 | 1.333 |
| 103 | 3 | 3.000 | 1.000 | -999.000 | -999.000 |
| 103 | 4 | -999.000 | -999.000 | 3.000 | 1.000 |
| 103 | 5 | .000 | 1.000 | -999.000 | -999.000 |
| 103 | 6 | -999.000 | -999.000 | .000 | 1.000 |
| 103 | 7 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 8 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 9 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 10 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 11 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 12 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 13 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 14 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 15 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 16 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 17 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 18 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 19 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 20 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 21 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 22 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 23 | 3.000 | 1.000 | -999.000 | -999.000 |
| 103 | 24 | -999.000 | -999.000 | 3.000 | 1.000 |
| 103 | 25 | -999.000 | -999.000 | -999.000 | -999.000 |
| 103 | 26 | 3.000 | 1.333 | -999.000 | -999.000 |
| 103 | 27 | -999.000 | -999.000 | 3.000 | 1.333 |
| 103 | 28 | 3.000 | 1.333 | -999.000 | -999.000 |
| 103 | 29 | -999.000 | -999.000 | 3.000 | 1.333 |
| 103 | 30 | 3.000 | 1.333 | -999.000 | -999.000 |



# Results Before (Top) and After (Bottom) TINTERVAL

| | Estimate | Posterior S.D. | One-Tailed P-Value | 95% C.I. Lower 2.5% | Upper 2.5% | Significance |
|---|---|---|---|---|---|---|
| Means | | | | | | |
| PINTIM | 2.214 | 0.146 | 0.000 | 1.925 | 2.504 | * |
| PPA | 1.500 | 0.100 | 0.000 | 1.305 | 1.699 | * |
| S1 | 0.337 | 0.050 | 0.000 | 0.242 | 0.437 | * |
| S2 | -0.022 | 0.043 | 0.308 | -0.105 | 0.066 | |
| S3 | 0.309 | 0.040 | 0.000 | 0.232 | 0.387 | * |
| S4 | 0.070 | 0.027 | 0.003 | 0.019 | 0.125 | * |

| | | | | | | |
|---|---|---|---|---|---|---|
| Means | | | | | | |
| PINTIM | 2.270 | 0.145 | 0.000 | 1.983 | 2.552 | * |
| PPA | 1.518 | 0.105 | 0.000 | 1.313 | 1.728 | * |
| S1 | 0.296 | 0.067 | 0.000 | 0.161 | 0.424 | * |
| S2 | -0.006 | 0.113 | 0.479 | -0.229 | 0.217 | |
| S3 | 0.231 | 0.066 | 0.001 | 0.100 | 0.360 | * |
| S4 | 0.097 | 0.045 | 0.011 | 0.013 | 0.190 | * |

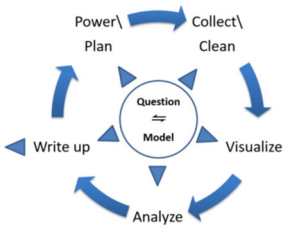
# Summary

- Unequal intervals between momentary assessments can make inferences about lagged effects challenging
- Mplus handles by using the TINTERVAL option to create equally spaced intervals
- Another approach to handling the issue of unequal time intervals between momentary assessments is would be to turn to continuous time modeling (Voelkle & Oud, 2013) but this is beyond the scope of this workshop



# Chapter Summary

- Full Cycle Approach to Modeling the Causal Process of a Continuous Outcome
- Example Data Set and Syntax in SPSS, R, and Mplus for Visualization, Analysis, and Power
- Other syntax (e.g., HLM, SAS, Stata) for the Time Course example can be found at: www.intensivelongitudinal.com



# Recommended Readings


- Raudenbush, S.W., & Bryk, A. (2002). Hierarchical Linear Models: Applications and Data Analysis Methods (2nd Ed.). Sage: London.
- Hox, J. J. (2010). *Multilevel analysis: Techniques and applications* (2nd Ed.). New York: Routledge.
- Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). Thousand Oaks, CA: Sage.




# ***Handling multiple time points per day***

# Chapter 4

**Five Fundamental Guidelines for Modeling Intensive Longitudinal Data**

# Five Guidelines

1. Allow for random effects
2. Even if temporal change per se is not of direct interest in your study, take the influence of time into account
3. Specify the appropriate number of independent units
4. Distinguish the between-person and within-person levels of analysis
5. Choose interpretable zero points for independent variables

# Five Guidelines

1. Allow for random effects

   Allow subjects to differ from one another in within-subject processes
2. Even if temporal change per se is not of direct interest in your study, take the influence of time into account

   Time as an explicit factor (i.e., predictor) in any model of interest
3. Specify the appropriate number of independent units

   Degrees of freedom: Total number of observations (N persons x T time points) not independently sampled, treat only upper-level units as independently sampled
4. Distinguish the between-person and within-person levels of analysis

   Can be different in size and in sign, ignoring them biases conclusions
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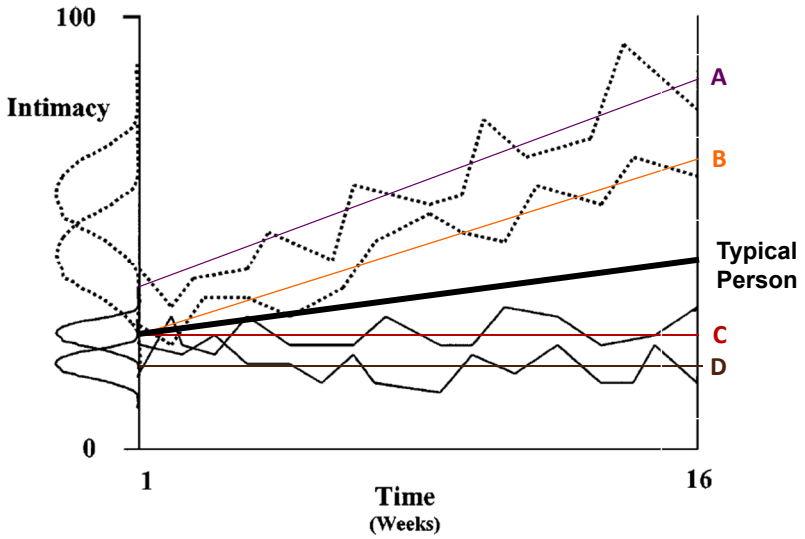
# 1. Fixed and Random Effects






# Why Should You Allow for Random Effects?

- There are two strong arguments, one statistical and one substantive, for including random effects for your within-person predictors:
  - Statistical: Several statisticians have shown that removing random slopes leads to type 1 errors for fixed effects due to downwardly biased SEs (e.g., Intimacy Tx example)
  - Substantive: Removing random slopes is the same as saying that the slope effect is the same for everyone (e.g., everyone has the same response to treatment) and is unlikely to be the case in the real world
  - ***Heterogeneity*** is generally the rule rather than the exception

# Summary

- Person-to-person heterogeneity in change over time and within-person processes is typically the rule rather than the exception
- Neglecting to include random effects tends to leave out an important, real-world source variation
- Using inferential tests to support the removal of random effects can suffer from low power
- When including multiple random effects in the same model leads to convergence issues, Bayesian estimation is the way to go (we'll cover Bayesian estimation later in the workshop)



# Five Guidelines

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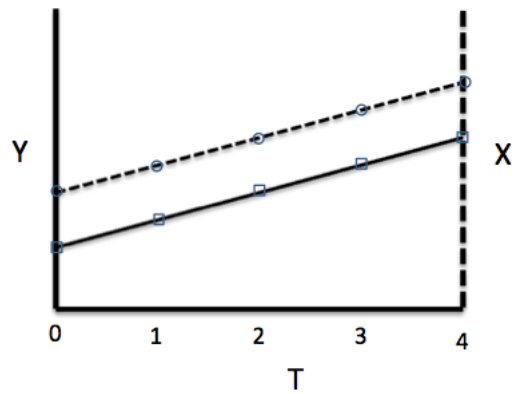
# 2. Modeling Time (A)

Correlation between X and Y is due to time

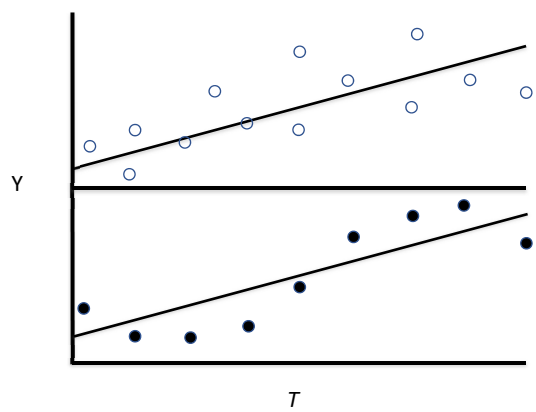



Thus, need to include time as a predictor in the model



# 2. Modeling Time (B)

Autocorrelation in Level-1 residuals




$\rho = 0.0$

$\rho = 0.9$

Thus, need to allow for Level-1 autocorrelation in the model

# Comments

- The role of time can be incorporated in two ways:
  - As an explicit predictor
  - As autocorrelation in the lower-level residuals
- While both theoretically can be included in the same model, sometimes a random time effect and residual autocorrelation can "fight" over the same variance; in these cases, there is an argument to be made for privileging heterogeneity



# Five Guidelines

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## 3. Units of Analysis

Number of Persons OR
Person x Time Points?

5-1 vs. 25-1
degrees of freedom?

5-1 is more defensible

| $ID_j$ | $T_i$ | $X_{ij}$ | $Y_{ij}$ | $W_j$ |
|---|---|---|---|---|
| 1 | 0 | $x_{11}$ | $y_{11}$ | $w_1$ |
| 1 | 1 | $x_{21}$ | $y_{21}$ | $w_1$ |
| 1 | 2 | $x_{31}$ | $y_{31}$ | $w_1$ |
| 1 | 3 | $x_{41}$ | $y_{41}$ | $w_1$ |
| 1 | 4 | $x_{51}$ | $y_{51}$ | $w_1$ |
| 2 | 0 | $x_{12}$ | $y_{12}$ | $w_2$ |
| 2 | 1 | $x_{22}$ | $y_{22}$ | $w_2$ |
| 2 | 2 | $x_{32}$ | $y_{32}$ | $w_2$ |
| 2 | 3 | $x_{42}$ | $y_{42}$ | $w_2$ |
| 2 | 4 | $x_{52}$ | $y_{52}$ | $w_2$ |
| 3 | 0 | $x_{13}$ | $y_{13}$ | $w_3$ |
| 3 | 1 | $x_{23}$ | $y_{23}$ | $w_3$ |
| 3 | 2 | $x_{33}$ | $y_{33}$ | $w_3$ |
| 3 | 3 | $x_{43}$ | $y_{43}$ | $w_3$ |
| 3 | 4 | $x_{53}$ | $y_{53}$ | $w_3$ |
| 4 | 0 | $x_{14}$ | $y_{14}$ | $w_4$ |
| 4 | 1 | $x_{24}$ | $y_{24}$ | $w_4$ |
| 4 | 2 | $x_{34}$ | $y_{34}$ | $w_4$ |
| 4 | 3 | $x_{44}$ | $y_{44}$ | $w_4$ |
| 4 | 4 | $x_{54}$ | $y_{54}$ | $w_4$ |
| 5 | 0 | $x_{15}$ | $y_{15}$ | $w_5$ |
| 5 | 1 | $x_{25}$ | $y_{25}$ | $w_5$ |
| 5 | 2 | $x_{35}$ | $y_{35}$ | $w_5$ |
| 5 | 3 | $x_{45}$ | $y_{45}$ | $w_5$ |
| 5 | 4 | $x_{55}$ | $y_{55}$ | $w_5$ |



## Comments

- Generally speaking, inferential tests involving degrees of freedom should be based on the number of participants (N) rather than number of participants * time points (N*t)
- Some packages (e.g., Mplus) use z-tests for fixed effects and thus degrees of freedom are not relevant (and the z- and t-distributions are almost equivalent when sample size N is large)

# Five Guidelines

1. Allow for random effects

   Allow subjects to differ from one another in within-subject processes
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   Time as an explicit factor (i.e., predictor) in any model of interest
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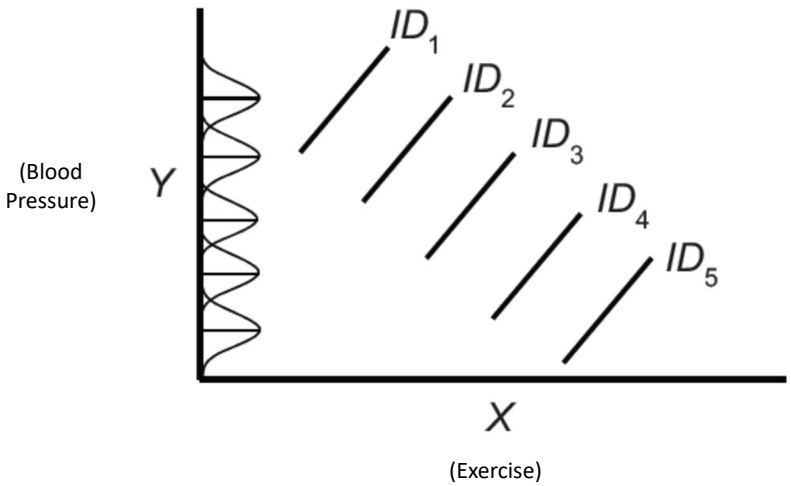
   Can be different in size and in sign, ignoring them biases conclusions
5. Choose interpretable zero points for independent variables



# 4. Differences Between and Within Persons

- Between-person differences: People can differ from each other
- Within-person differences: Each person can differ across time points
- Carefully distinguish these levels
- Multilevel analysis distinguishes between these two levels for the outcome <u>but does not do so automatically for the predictor</u>

# 4. X to Y Relationship Exists at Both Levels






# 4. X to Y Relationship Exists at Both Levels

- Between-person associations based on observational data are prone to between-person confounders
- Within-person associations cannot be accounted for by stable person or situation characteristics (i.e., no bias of level-1 coefficients due to omitted level-2 variables)

## Comments

- The relationships between X and Y within-person versus between-person need not be the same size or even the same sign
- If you don't separate within from between, you will be left with a single coefficient that will be an uninterpretable and confounded weighted blend of both effects
- In this workshop, we emphasize and privilege the within-person links between predictors and outcomes (over their between-person counterparts) because that is what you should be after if you have conducted an IL study



## Five Guidelines

1. Allow for random effects

   Allow subjects to differ from one another in within-subject processes
2. Even if temporal change per se is not of direct interest in your study, take the influence of time into account

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5. Choose interpretable zero points for independent variables

## Goal Is To Know Zero

- Importance of knowing what zero means on all predictors in a model, for both time-varying predictors as well as time itself



## 5. Interpretable Zero Points for Predictors

- Also called centering
- Centering involves changing the zero point on a variable, usually by subtracting some value from the raw score
- Leaving the Xs and Ws in their raw form is often not a good idea
- We saw examples of this in the Time Course and Process examples
  - Changing the metric of time
  - Person-mean centering key time-varying predictors

# 5. Interpretable Zero Points for Predictors

Time should also have a meaningful zero point

- *Initial Time:*
  Most frequently used when there is systematic change (e.g., growth)
- *Middle Time:*
  Good when trajectories are flat and nothing much happens over time (e.g., typical daily diary design)
- *Endpoint:*
  Good when heading towards something final (e.g., surgery, transplantation, exam)



# Comments

- It is generally a good thing to know what the zero points on all predictors mean as it helps with interpretation of coefficients in regression-based models
- It is also generally good to make sure 0 has an interpretable meaning via centering or at least making sure 0 is in the range of your data
- Unlike in single-level regression, there are several options for centering predictors that vary both within- and between-person

## Chapter Summary

- It's probably safe to say that these five fundamental guidelines are relevant for all longitudinal designs
- It is worth noting that neglecting to include random effects is being attended to more and more by journal editors and reviewers



## Recommended Readings

- Allow for random effects:
  - Barr, D.J., Levy, R., Scheepers, C., & Tily, H.J. (2013). Random effects structure for confirmatory hypothesis testing: keep it maximal. *Journal of Memory and Language, 68,* 255–278.
  - Matuschek, H., Kliegl, R., Vasishth, S., Baayen, H., Bates, D.M. (2017). Balancing type I error and power in linear mixed models. *Journal of Memory and Language, 94,* 305–315.
  - Bell, A., Fairbrother, M., & Jones, K. (2019). Fixed and random effects models: making an informed choice. *Quality & Quantity, 53*, 1051–1074.

# Recommended Readings

- Account for time in your model:
  - Curran, P.J., & Bauer, D.J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology, 62*, 583-619.
- Distinguish within- versus between-person levels of analysis
  - Raudenbush, S.W., & Bryk, A. (2002). Hierarchical Linear Models: Applications and Data Analysis Methods (2nd Ed.). Sage: London.
  - Molenaar, P.C.M., & Campbell, C.G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science, 18*, 112-117.



# Recommended Readings

- Have interpretable zero points on all predictors
  - Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). Thousand Oaks, CA: Sage.
  - Cohen, J., Cohen, P., West, S., & Aiken, L. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd Ed). Hillsdale, NJ: Lawrence Erlbaum Associates.