TWO-DAY DYADIC DATA ANALYSIS WORKSHOP

Randi L. Garcia

Smith College

UCSF January 9th and 10th

@RandiLGarcia RandiLGarcia

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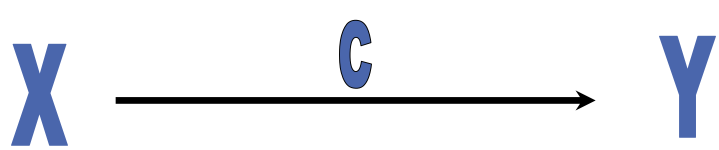
DAY 2

- Mediation in the APIM
- Moderation in the APIM
- Dyadic Growth Curve Modeling
- Other Longitudinal Models for Dyads

MEDIATION

Mediation



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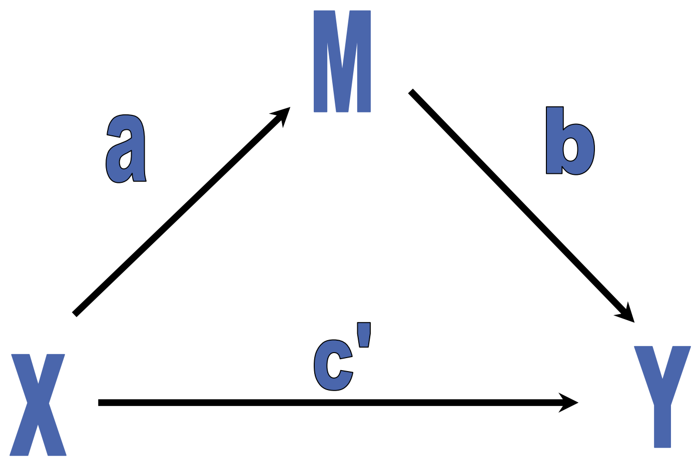
Mediation



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The Four Paths

- X → Y: path c
- X → M: path a
- M → Y (controlling for X): path b
- X → Y (controlling for M): path c'

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Decomposition of Effects

- Total Effect = Direct Effect + Indirect Effect

$$c = c' + ab$$

- Note that

$$ab = c - c'$$

- Percent of the total effect mediated:

$$ab/c \; *100$$

or

$$(1 - c'/c) *100$$

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Strategies to Test null hypothesis: ab = 0

- Sobel test
- Bootstrapping
- Monte Carlo Method

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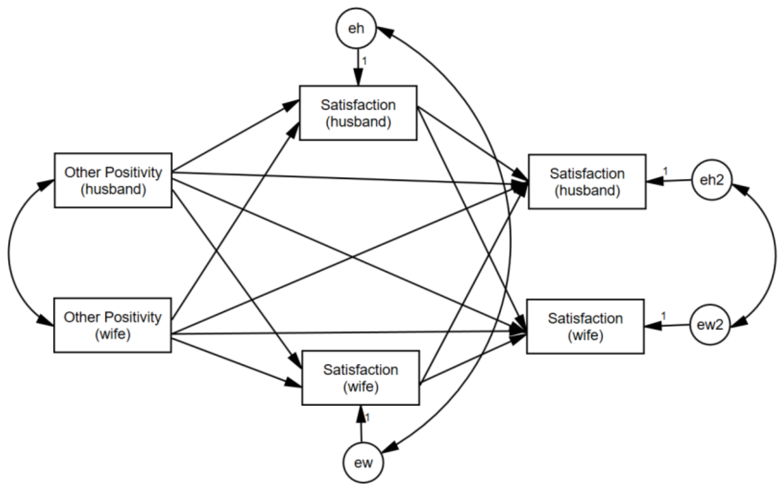
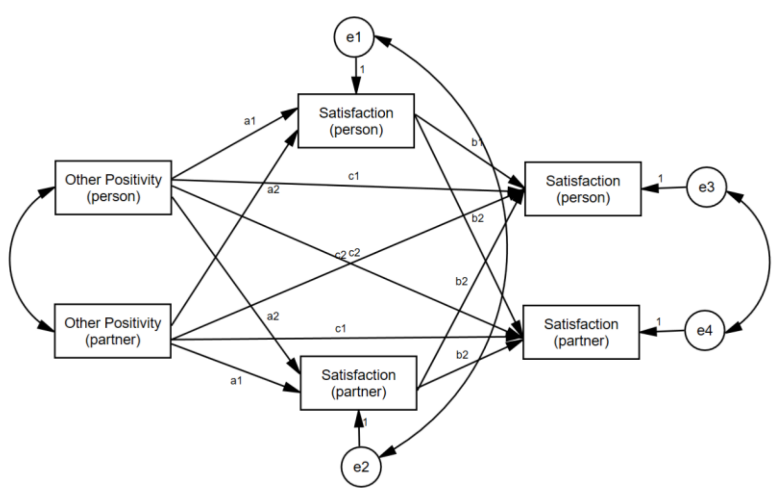
Example-Tension, Distinguishable



Example-Tension, Indistinguishable



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MODERATION

Centering Review

$$y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + b_3 X_{1i} X_{2i} + e_i$$

b_1 = effect of X_1 when X_2 is zero

b_2 = effect of X_2 when X_1 is zero

- The meaning of a main effects depends on the meaningfulness of zero of the other variable.
- To make zero meaningful
  - Grand-mean center

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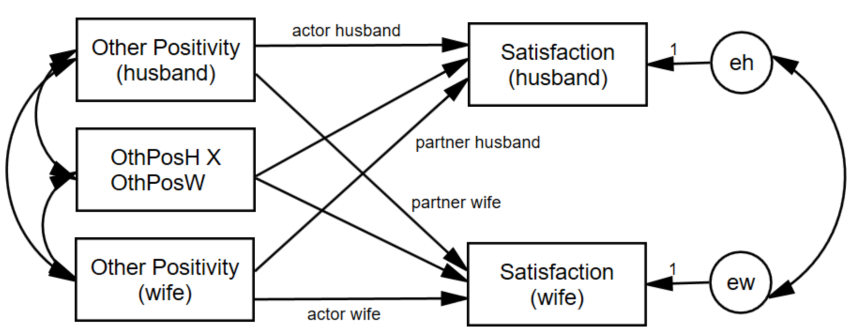
Actor-Partner Interactions

- We can ask, does the ***actor effect*** get stronger or weaker as the ***partner variable*** goes up?



Dichotomous Within-Dyads Moderator

- The distinguishing variable is a moderator.
- The two partners each have a score but across dyads the average scores are the same (e.g., gender in heterosexual couples)
- If dyad members are distinguishable, two moderation effects
  - Moderates the actor effect
  - Moderates the partner effect

Between-Dyads Moderator

- One moderation variable (one score per dyad)
- Examples
  - Years married
  - Couple level treatment
  - Gay vs. lesbian couples
  - Twins: separated at birth vs. raised together

Between-Dyads Moderator

- Indistinguishable: Two moderation effects
  - Moderates the actor effect
  - Moderates the partner effect
- Distinguishable: Four moderation effects
  - Moderates the actor effect for each member
  - Moderates the partner effect for each member

Mixed Moderator

- The two partners each have a score, and the average score varies across dyads. Thus, there are really **two moderator variables** (actor and partner).
- Indistinguishable: Four moderation effects
  - actor effect moderated by each member's closeness
  - partner effect moderated by each member's closeness
- Distinguishable: Eight moderation effects
  - Each of the above also moderated by member type (e.g., husband and wife)
- It would be great if we could simplify, find patterns among, these effects.

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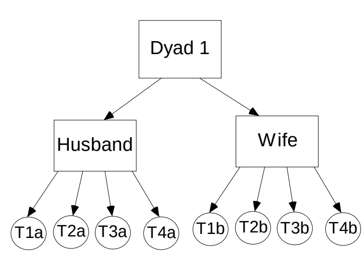
LONGITUDINAL MODELS

Examples of Over-Time Dyadic Data

- Daily diary reports of relationship experiences from both members of heterosexual dating partners over 14 days
- Repeated measures experiment where dyads interact with each other multiple times and make ratings after each interaction
- Daily reports of closeness from both members of college roommate dyads

Basic Data Structure

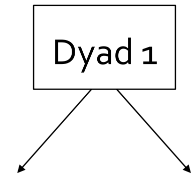
- The three-level nested myth: Time is nested within person and person is nested within dyad



- Three-level nested only if the four time points differ such that T1a ≠ T1b, T2a ≠ T2b, etc.

Basic Data Structure

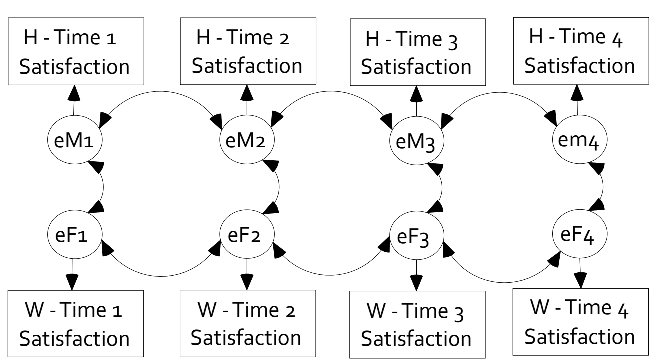
- In most cases the two dyad members are measured at the same time points, so Time is *crossed* with person.



	Husband	Wife
T1	H_T1	W_T1
T2	H_T2	W_T2
T3	H_T3	W_T3
T4	H_T4	W_T4

Basic Data Structure

- This two-level crossed structure results in an error structure in which the residuals may be correlated both
  - A) across dyad members
  - B) across time



Types of Over-Time Models

- Repeated Measures Model
  - Interest only in the effects of "time" across persons and dyads.
- Growth Curve Model
  - Are there linear changes over time in the outcome variable?
- Stability and Influence Model
  - Stability: Does Person A's score at time 1 predict Person A's score at time 2?
  - Influence: Does Person A's score at time 1 predict Person B's score at time 2?
- Standard APIM
  - Different variables as the predictors and at the outcome
  - Does Variable 1 predict Variable 2?

Examples

- Repeated Measures
  - The effect of day of the week (weekday versus weekend) and gender
- Growth Curve Model
  - Individual growth curve
  - Dyadic growth curve
    - Satisfaction over time
- Stability and Influence Model
  - Prior satisfaction predicts current satisfaction
- Standard APIM
  - Actor and partner conflict predict satisfaction

Types of Variables

- Time Invariant
  - Do not change over time
  - Measured at one time point only (typically the beginning of the study)
  - E.g., gender, attachment style, race
- Time Varying
  - Measured at each time
  - E.g., daily mood, twice-weekly reports of friendship
  - Outcome variable must be time varying

How Many Time Points?

- Depends on type of analysis
  - The more complicated the model, the more time points needed
- Minimum
  - Repeated measures: Two
  - Other models: Three
- More is better.
- Ultimately depends on the model, the research setting, and research questions.

Example: Daily reports of conflict, support, and relationship satisfaction

- Kashy data set
- 103 heterosexual dating couples
- Assessed once daily for 14 days
- Completed daily reports of relationship satisfaction and amount of conflict that day
  - Satisfaction and Conflict are time-varying
- Pretest data for attachment avoidance
  - Measured for both people
  - Time invariant

Person Period Pairwise Dataset

- Each Person by Time combination has its own record
  - Person has its own variable (e.g., Person = 1, 2)
  - Occasion has its own variable (e.g., Day = 1 to 14)
- Required for Multilevel Modeling
- We'll look at it when we get to R

Modeling Two Growth Curves

$$Y_{Wti} = c_{Wi} + b_{Wi}T_{ti} + e_{Wti}$$

$$Y_{Mti} = c_{Mi} + b_{Mi}T_{ti} + e_{Mti}$$

Intercepts

c_{Wi} = Predicted value of women's satisfaction at study midpoint for dyad i

c_{Mi} = Predicted value of men's satisfaction at study midpoint for dyad i

Slopes

b_{Wi} = Average change in women's satisfaction over time for dyad i

b_{Mi} = Average change in men's satisfaction over time for dyad I

Errors at each time point

Women = e_{Wti}

Men = e_{Mti}

Correlation of the Residuals

- If the man reports more satisfaction for a particular day than would be expected given the overall effect of time, does the woman also report more satisfaction for that day?

Random Effects: Variances

- There are six variances
  - two intercepts
    - Do men (and women) differ from each other in their "time zero" predicted score?
  - two slopes for time
    - Do the slopes for men (and women) differ?
  - two error (distance from the line) variances
    - Error variances (deviations from the slope) for men and women

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Random Effects: Within Person Correlations

- Man intercept-slope correlation
  - If a man is highly satisfied at the study midpoint, is his change in satisfaction steeper?
- Woman intercept-slope correlation
  - If a woman is highly satisfied at the study midpoint, is her change in satisfaction steeper?

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Four Between-Person Correlations

- Correlation of the intercepts between partners
  - Overall, do women who have higher levels of satisfaction at the study midpoint tend to have male partners who are also higher in satisfaction at the study midpoint?
  - That is: Is there a correspondence between level of satisfaction?
- Correlation of the slopes
  - Do women whose satisfaction changes over time tend to have male partners whose satisfaction also changes over time?
  - That is: Is there a correspondence between linear change in satisfaction?
- Two slope-intercept correlations
  - Do women with higher levels of satisfaction have male partners who increase or decrease?
  - Do men with higher levels of satisfaction have female partners who increase or decrease

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Estimates of Random Effects

- The random option specifies the variances (given as standard deviations) and covariances (given as correlations) between the intercepts and slopes

			Man Intercept	Woman Intercept	Man Time Slope	Woman Time Slope
	Man Intercept	***sd***				
	Woman Intercept	***sd***	***r***			
Rho	**Man Slope**	***sd***	***r***	***r***		
	Woman Slope	***sd***	***r***	***r***	***r***	
	Residual	***sd***				

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Why Random Effects Are Important

- If the wrong random model is selected (one that is too complicated), the solution may not converge.
- If the wrong model is selected (one that is too simple), significance tests of fixed are wrong.
  - Standard errors are biased
- They are interesting in their own right.
  - Answers interesting questions about individual differences and similarity of dyad members.
  - Points to possible moderators.
- Can be combined with fixed effects for interpretation.

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LONGITUDINAL APIM

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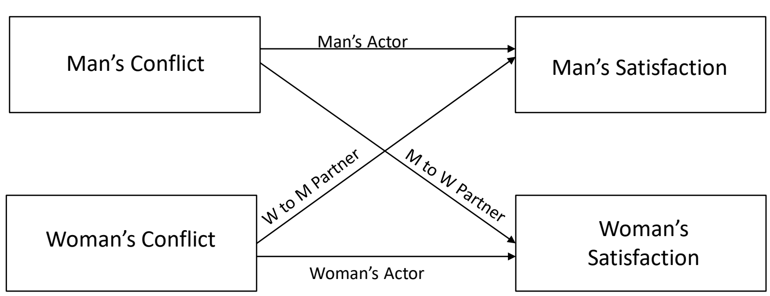
Longitudinal APIM



- This is old hat—but the random actor and partner effects are the most interesting!

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Data Structure

ID	Dyad	Partnum	Time	Actor Satis.	Actor Conflict	Partner Conflict
25	13	1	1	2	5	5
25	13	1	2	5	2	3
25	13	1	3	7	5	6
25	13	1	4	4	7	8
26	13	2	1	3	5	5
26	13	2	2	6	3	2
26	13	2	3	8	6	5
26	13	2	4	2	8	7

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STABILITY AND INFLUENCE

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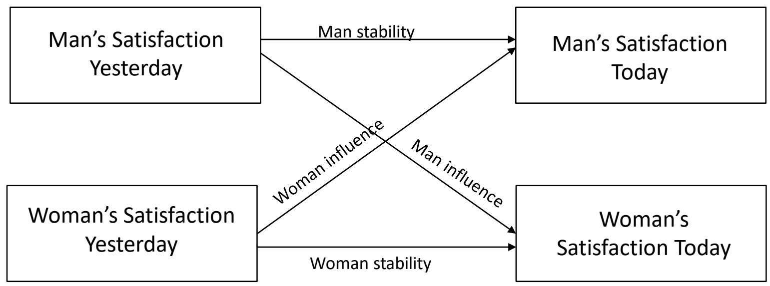
Stability-Influence: APIM



1. We can measure stability and influence for each man and each woman:
2. Is stability moderated by gender?
3. Is influence moderated by gender?

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Data Structure

ID	DYADID	PERSON	DAY	ASATISF	ASATISF Lagged	PSATISF Lagged
25	13	1	1	2	.	.
25	13	1	2	5	2	3
25	13	1	3	7	5	6
25	13	1	4	4	7	8
26	13	2	1	3	.	.
26	13	2	2	6	3	2
26	13	2	3	8	6	5
26	13	2	4	2	8	7

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COMMON FATE MODEL

Dyadic Models

- The Common Fate Model (CFM) is perhaps the oldest dyadic model (Kenny & La Voie, 1985).
- However, CFM used empirically only a handful of times.
- The APIM which is regularly used (at least 95% of the time) may often be theoretically inappropriate.

- Paper: Ledermann, T., & Kenny, D. A. (2012). The common fate model for dyadic data: Variations of a theoretically important but underutilized model. *Journal of Family Psychology*, 26, 140-148.

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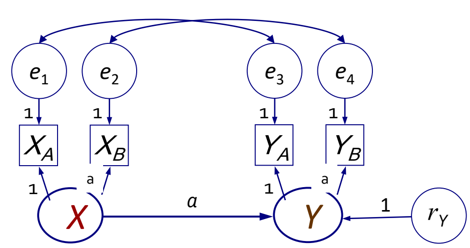
The CFM as a SEM Model

- The Common Fate Model (CFM) consists of 2 latent variables (X and Y) and 2 indicators (X_A and X_B, Y_A and Y_B) where A and B are distinguishable members of a dyad.



- The model has 1 df.
- That 1 *df* can be viewed as testing if the loading on X_B and Y_B are not equal to one. If fit is poor, the two loadings can be fixed to the same value.

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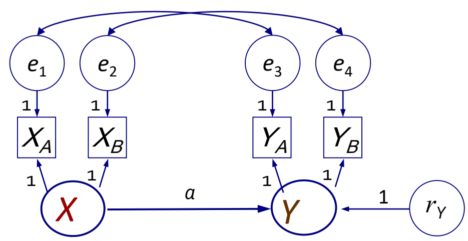
Indistinguishable Members

- Five equality constraints are made: equal X and Y intercepts, equal X and Y error variances, and equal error covariances.



With these constraints, the model has zero *df*.

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When Does the CFM Make Sense?

- The latent variable represents a dyadic construct ("us," "we," or "the relationship" instead of "you" or "him or her") or shared external influences.
- The causal relation between the variables is presumed to be at the level of the dyad.

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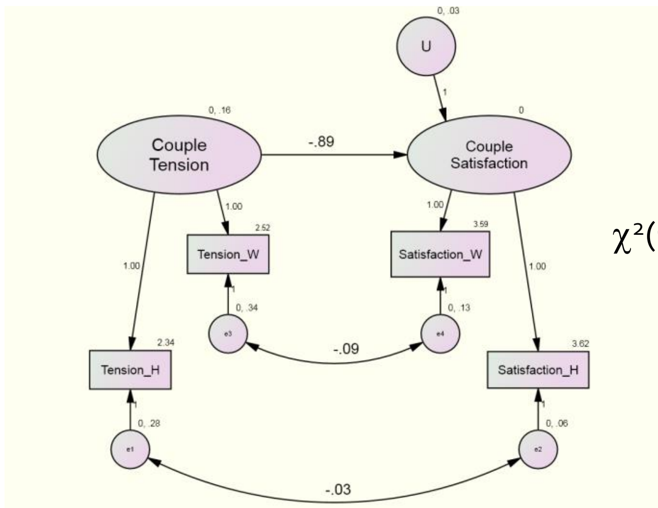
When Does the CFM **Not** Make Sense?

- The variable measures an individual characteristic: how the individual feels or the individual's personality.
- The two dyad members scores correlate weakly with each other. If the correlation between the two X or Y scores is weak ($r < .30$), there can be estimation difficulties.

Advantages of the CFM over the APIM

- Has a true "dyad-level" effect, not individual-level effects
- Parsimony: For moderation and mediation in the APIM, there can be up to 8 effects. For the CFM, there is just one. Thus, the CFM is simpler.

Example: Standard CFM



$\chi^2(1) = 0.179, p = .672$

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(Current/Known) Limits of R

- Indistinguishable dyads
  - Needs to be analyzed in SAS, HLM, or MLwiN because constraints on the variance-covariance matrix or random effects are needed.
- P-values for random effects

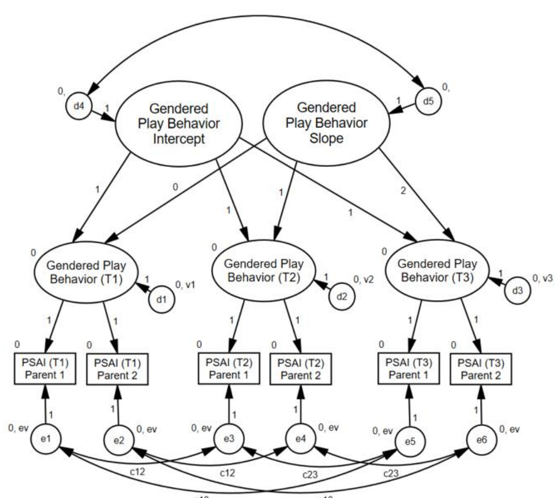
Topics Not Covered

- Indistinguishable dyads
- Time-varying moderators
  - E.g., daily mood moderates daily satisfaction
- Non-linear growth curve models
  - Transformations
  - Periodic effects
  - Cubic, quadratic
- More complicated error models
- Longitudinal models with non-normal outcomes—but `glmer()` can handle them

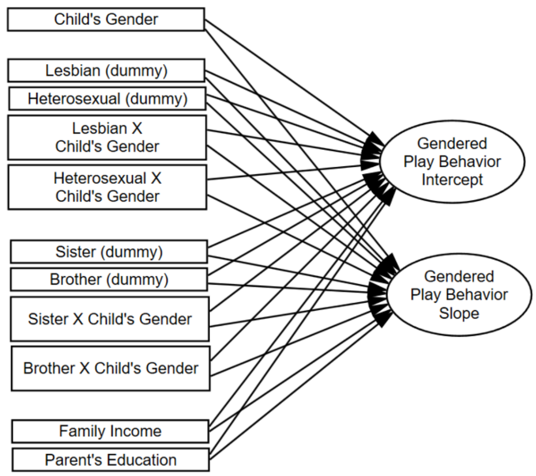
BONUS: COMMON FATE GROWTH MODEL

Children's Gendered Behavior Overtime

Goldberg & Garcia (2016)



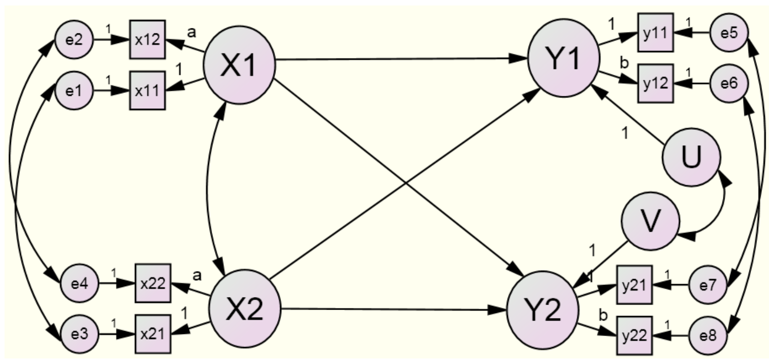
Children's Gendered Behavior Overtime



BONUS: OTHER SEM DYAD MODELS

Latent Variable APIM

- **Advantages over Traditional APIM**
  - Effects may be larger.
  - Effects are less biased.



The Mutual Influence Model