Modeling Psychological Subgrouping using Multiple Demographic Composition Variables

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Today's Talk

- Demographic differences in Groups
  - Introduction to the Group Actor Partner Interdependence Model (GAPIM)
- Demographic subgrouping
  - Incorporating multiple demographics with GAPIM
  - Group "Faultlines"
  - Empirical tests of different measurement strategies

Consequences of Difference in Groups

- Social Categorization Perspective
  - Group heterogeneity is negatively associated with group liking. (Harrison et al., 1998; Jackson et al., 1993; O'Reilly et al., 1989)
    - Attraction Paradigm (Byrne, 1971), Self-Categorization Theory (Turner et al., 1987) and Social Identity Theory (Tajfel & Turner, 1986)

- Information/Decision making perspective
  - Group heterogeneity is positively related to productivity (Williams & O'Reilly, 1998)
    - Sommers (2006) found that information was retained more when juries were diverse
    - Evidence is mixed (van Knippenberg, De Dreu & Homan, 2004)

Consequences of Difference in Groups

- **Social Categorization Perspective**
  - **Group heterogeneity is negatively associated with group liking. (Harrison et al., 1998; Jackson et al., 1993; O'Reilly et al., 1989)**
    - **Attraction Paradigm (Byrne, 1971), Self-Categorization Theory (Turner et al., 1987) and Social Identity Theory (Tajfel & Turner, 1986)**

- Information/Decision making perspective
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Effects of the Others in a Group

- The Attraction Paradigm and Self-Categorization Theory place importance on interpersonal perceptions of similarity
  - First understanding how differences in groups lead to dyadic perceptions of similarity.
- Conceptualizing demographic differences between group members is a complex issue, especially with dyadic outcomes
- Demographics of the *other* group members may affect dyadic perceptions of similarity by potentially highlighting or dampening certain types of difference.

Conceptualizations of Difference

- Summary measures
  - Mean differences
    - The effect of the group's average, sometimes called group climate (Florin, Giamartino, Kenny, & Wandersman, 1990)

Traditional Multilevel Modeling (MLM) of Groups

- Variables X_{ik}, person i's gender in group k (level 1) and $\bar{X}_{.k}$, group k's mean gender (level 2) to predict Y.

- Or $X_{ik} - \bar{X}_{.k}$ (or X_{ik} "group mean centered") and $\bar{X}_{.k}$ to predict Y.

- Problems with the Traditional MLM Formulation:
  - Part-whole problem.
  - What about other effects of X, especially diversity in the Xs (or the similarity of the Xs)?

Conceptualizations of Diversity

- Distance or dispersion measures
  - Sums of multiple proportions
    - Blau's (1977) and Teachman's (1980) indexes
  - Relational Demography
    - The effect of a person's fit into the group or the person's similarity to the other members (Elfenbein & O'Reilly, 2007)

Conceptualizations of Diversity

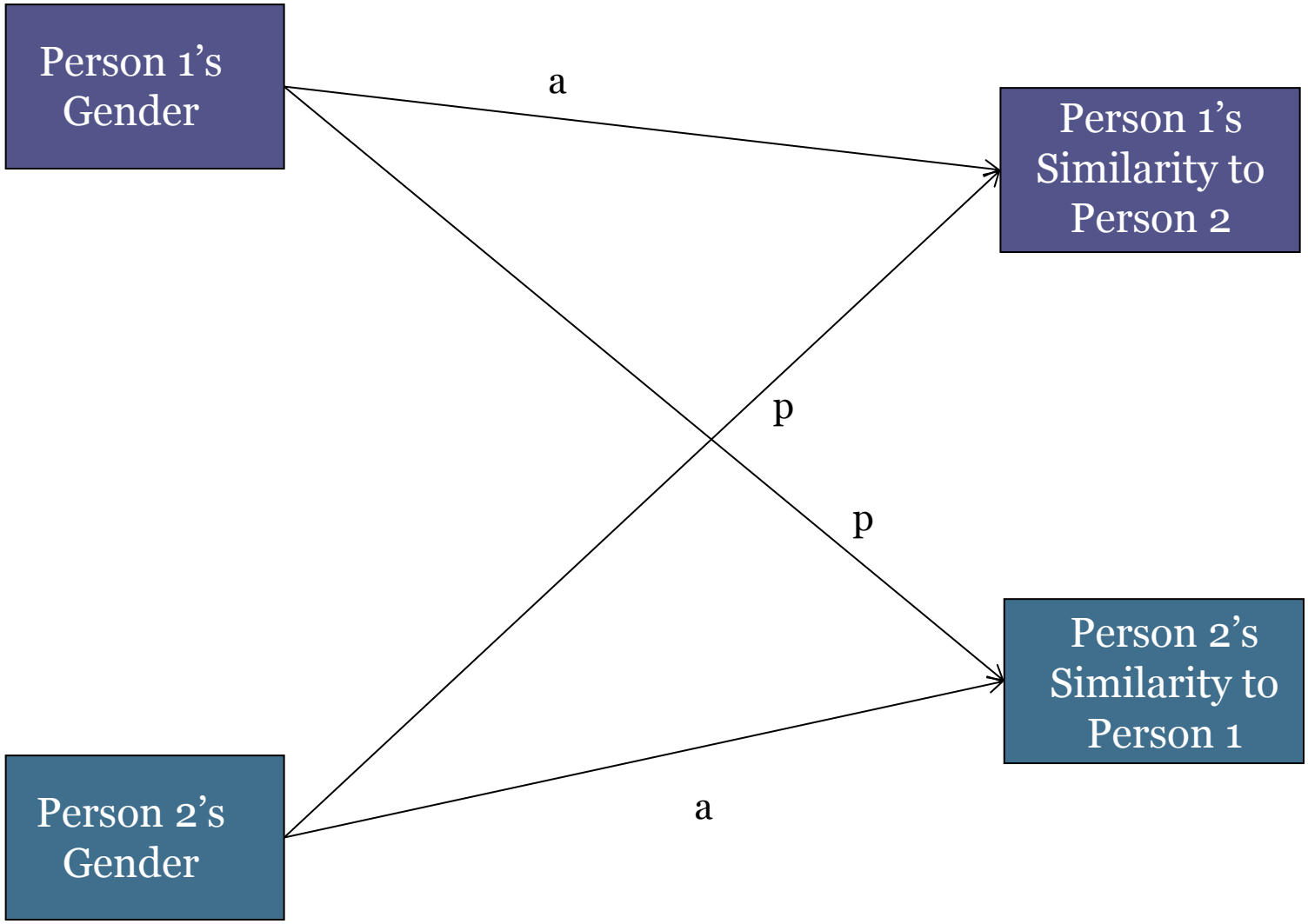
- Measuring group diversity
  - Group variance in demographic variable

$$S_j{}^2 = \frac{\sum_{i=1}^{n} (X_i - \bar{X})^2}{n-1} = \frac{\sum_{i=1}^{n-1} \sum_{k=i+1}^{n} (X_i - X_k)^2}{[n(n-1)]}$$

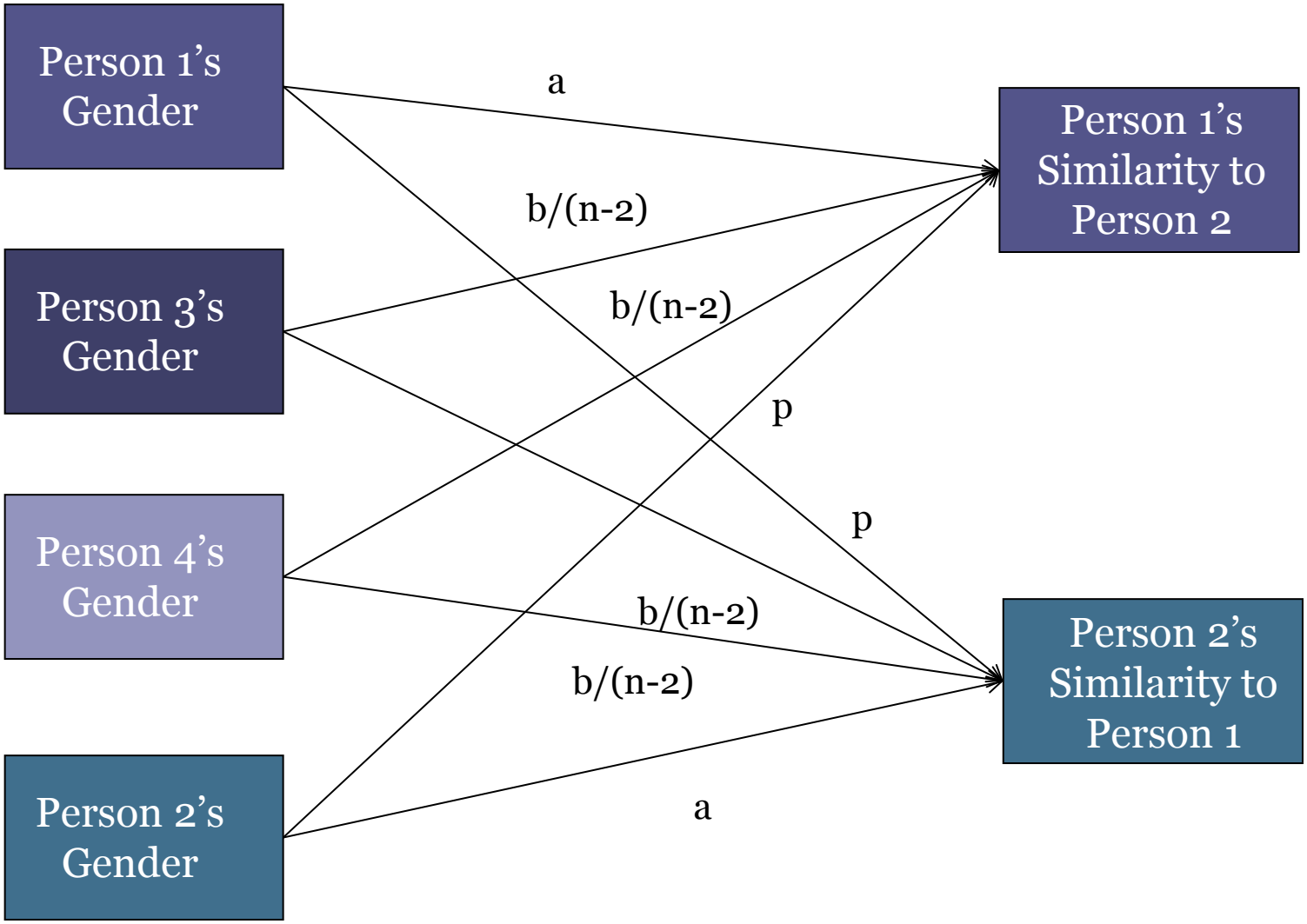
    - where n is the groups size

  - We can decompose *Diversity* depending on the level of measurement of our outcome variable

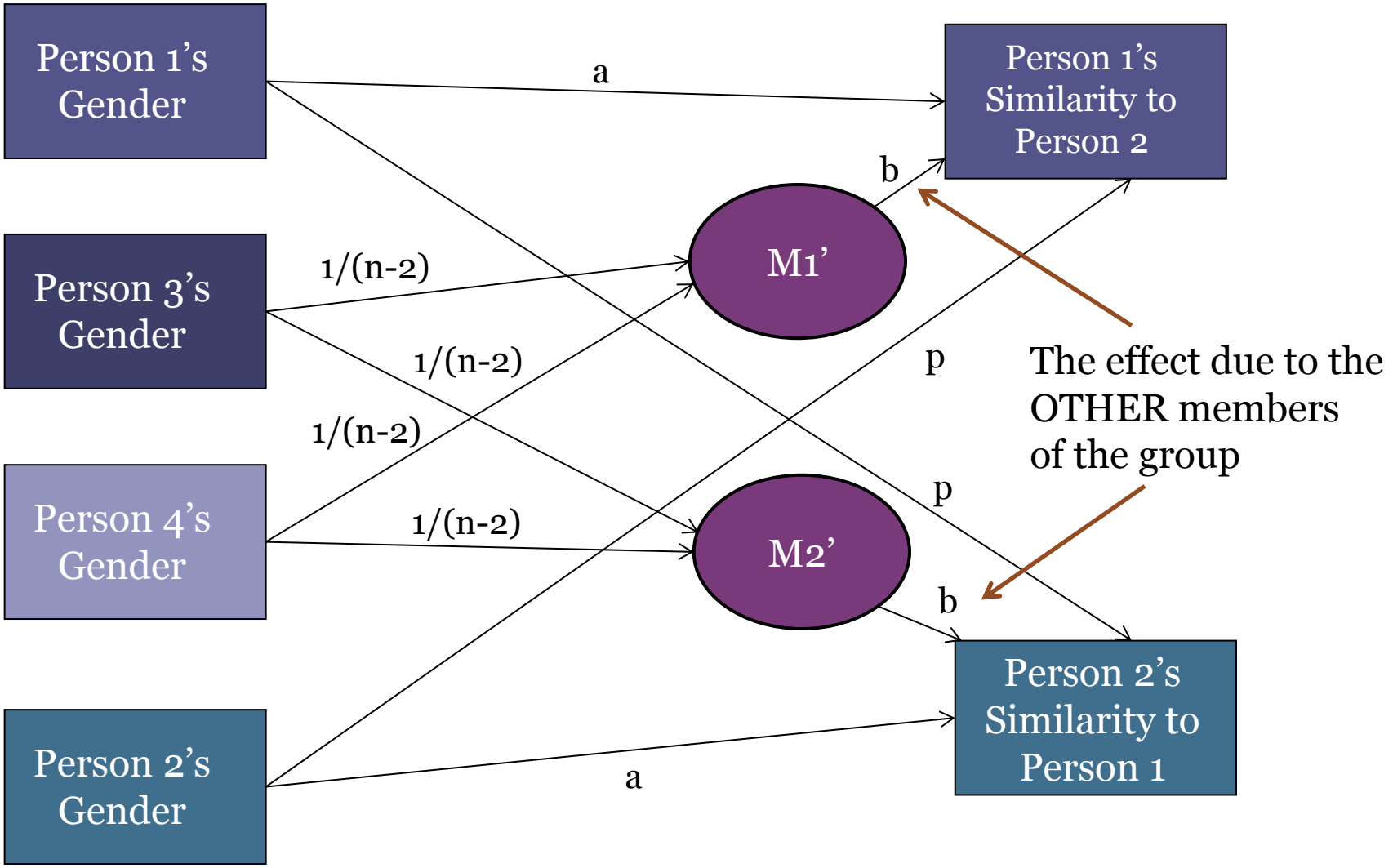
GAPIM


Person 1's Gender
a
Person 1's Similarity to Person 2
p
p
Person 2's Similarity to Person 1
Person 2's Gender
a

GAPIM


Person 1's Gender
Person 3's Gender
Person 4's Gender
Person 2's Gender
Person 1's Similarity to Person 2
Person 2's Similarity to Person 1
a
b/(n-2)
b/(n-2)
p
p
b/(n-2)
b/(n-2)
a

GAPIM


Person 1's Gender
Person 3's Gender
Person 4's Gender
Person 2's Gender
Person 1's Similarity to Person 2
Person 2's Similarity to Person 1
M1'
M2'
a
b
1/(n-2)
1/(n-2)
1/(n-2)
1/(n-2)
p
p
a
b
The effect due to the OTHER members of the group

GAPIM-D

- Mixed Linear Model with 7 fixed effects, 4 random effects, 2 covariances of random effects

$$Y_{ijk} = b_0 + b_1X_{ik} + b_2X_{jk} + b_3X_{ijk}' + b_4I_{ijk} + b_5I_{i.k} + b_6I_{.jk} + b_7I_{ijk}' + e_{ijk}$$

- b_1: the effect of a person's own gender, the *actor effect*;
- b_2: the effect of the partner's gender, the *partner effect*;
- b_3: the effect of the average gender of the other $n - 2$ members of the group, the *others effect*;
- b_4: the effect of how similar in gender person i is to person k, *dyadic similarity effect*;
- b_5: the average similarity of person i's gender to the gender of the other $n - 2$ members of the group, the *actor similarity*;
- b_6: the average similarity of person k's gender to the gender of the other $n - 2$ members of the group, the *partner similarity;*
- b_7: the average similarity of the genders of all possible pairs of $n - 2$ others in the group, the *others' similarity*.

GAPIM-D

- Mixed Linear Model with 7 fixed effects, 4 random effects, 2 covariances of these random effects

$$Y_{ijk} = b_0 + b_1X_{ik} + b_2X_{jk} + b_3X_{ijk}' + b_4I_{ijk} + b_5I_{i.k} + b_6I_{.jk} + b_7I_{ijk}' + e_{ijk}$$

- Plus the Social Relations Model (SRM) random effects to model the nonindependence
  - σ_μ^2: Group variance
  - σ_α^2: Actor variance
  - σ_β^2: Partner variance
  - σ_γ^2: Relationship variance (error)
  - $\sigma_{\alpha\beta}$: Generalized reciprocity
  - $\sigma_{\gamma\gamma}$: Dyadic reciprocity

Multiple Composition Variables

- People have multiple characteristics that may influence how they categorize themselves and others in small groups. (Brewer, 1995)

- Researchers have recently called for attention to how multiple types of composition variables affect group dynamics simultaneously (Lau & Murnighan, 1998; Lau & Murnighan, 2005; Shaw, 2004; Thatcher, Jehn, & Zanutto, 2003; van Knippenberg, Dawson, West, & Homan, 2011)

Group Faultline Strength

- “Groups that encompass an identical array of demographic attributes collectively can still have markedly different dynamics if those characteristics are distributed differently among the individuals in a group” (p. 327, Lau & Murnighan, 1998)

- Differences between two group members belonging to different gender groups might be enhanced if these same two group members also belong to different racial groups.

Faultline Models

- Parallel Interaction Model
  - Interactions of like GAPIM terms across variables
    - Actor race X actor gender
    - Partner race X partner gender
    - Others race X others gender
    - Dyadic similarity race X dyadic similarity gender
    - Actor similarity race X actor similarity gender
    - Partner similarity race X partner similarity gender
    - Others similarity race X others similarity gender

Faultline Models

- Shaw's (2004) Faultline Strength, FLS
  - Combines a group's internal subgroup alignment…

$$IA_{men.race.obs} = \sum(O_{wi} - E_{wi})^2 / E_{wi},$$
for i = 1 (Black) to 2 (White)

  - and cross-subgroup alignment…

$$CGAI_{gender} = (N_{fW} \times N_{mW} + N_{fB} \times N_{mB})/(N_f \times N_m)$$

Faultline Models

- Shaw's (2004) cont.

$$FLS_{gender} = IA_{gender} \times \left(1 - CGAI_{gender}\right), \text{ then}$$

$$FLS = \left(FLS_{gender} + FLS_{race}\right)/2$$

- When internal alignment is high and cross-subgroup alignment is low this is when *FLS* is the highest.

- FLS_{gender} and FLS_{race} would equal the same value if there were perfect alignment of faultline strength is at its maximum.

Faultline Models

- Thatcher et al.'s (2003) measure, *Fau*—proportion of variance explained by each split is given by the following equation:

$$Fau_g = \left(\frac{\sum_{j=1}^{2} \sum_{k=1}^{2} n_k^g \left(\bar{x}_{.jk} - \bar{x}_{.j.} \right)^2}{\sum_{j=1}^{2} \sum_{k=1}^{2} \sum_{i=1}^{n_k^g} \left(\bar{x}_{ijk} - \bar{x}_{.j.} \right)^2} \right), \qquad g = 1, 2, \ldots S$$

- where n_k^g is the number of members in the k^{th} subgroup on the g^{th} split.
- S is the number of ways the group can be split into 2 subgroups.
- x_{ijk} is the value of the j^{th} characteristic for the i^{th} member of the k^{th} subgroup
- Denominator is the total variance in race and gender
- Numerator is the variance in race and gender across subgroups.
- Maximum *Fau* is taken as **group's measure** of Faultline strength

Study 1

Round-robin design

Combined race and gender composition

Method

- Collected by Culhane, Hosch, and Weaver (2004)
- Gathered from El Paso, Texas jury pool
- 134 6-person juries from the jury pool
  - 54.6% female, 58.5% Hispanic, 31.3% White, 3.9%, Black/African-American, and 2.2% Asian American or Native American.
- Due to missing data in ethnicity 122 groups used in the analyses
- Mock case: Theft
- Jurors rated similarity in a round-robin fashion

Method (cont.)

- Composition of gender and ethnicity was used
  - Women are coded as -1 and men are coded as 1
  - Hispanic jurors coded as -1 and Non-Hispanic jurors coded as 1

Group Composition Results

	Gender	Ethnicity
Actor		
Partner		
Others		
Dyadic Similarity		
Actor Similarity		
Partner Similarity		
Others Similarity		

* $p < .05$, ** $p < .01$, *** $p < .001$

Model Comparisons

Model	SABIC
Additive Model	11111.56
Dyadic Model	**11099.68**
Parallel Interaction Model	11104.80
FLS Model	11101.63
Fau Model	11101.73

Summary

- The Dyad Model was the best fitting model
- Some evidence for non-additive effects of race and gender composition.
  - Parallel Interaction Model found an interaction of actor race and actor gender.
- Faultline strength measures did not predict dyadic perceptions of similarity.

Study 2

Repeated measures design

Manipulated race and gender composition of perceptive groups

Method

- A total of 156 participants
  - Only those who self-identified as either White/European-American or Black/African-American were included in the analyses (N = 116)
- 20 Black/African American/Caribbean Americans (17.2%), 96 White/European Americans
- 52 men (44.8%) and 64 women
- Ages ranged from 18 to 42

Method

- Participants are given questionnaires with faces of 4 other "participants" (and their own) who they believe they will soon discuss a topic with
  - The gender (male vs. female) and racial (Black vs. White) compositions of the groups were manipulated.

- Were asked how similar they felt towards each of the other group members.

Person A

Person B

Person C

Person D

Person E

Instructions: Please answer the following questions about Person B. If you are Person B then please skip the fist question and answer the character questions about yourself.

	Not at all	Very slightly	A little	Moderately	Quite a bit	Extremely
1: How similar do you feel to **Person B?**	○	○	○	○	○	○

Person A

Person B

Person C

Person D

Person E

Instructions: Please answer the following questions about Person C. If you are Person C then please skip the fist question and answer the character questions about yourself.

	Not at all	Very slightly	A little	Moderately	Quite a bit	Extremely
1: How similar do you feel to **Person C?**	○	○	○	○	○	○

Person A

Person B

Person C

Person D

Person E

Instructions: Please answer the following questions about Person B. If you are Person B then please skip the fist question and answer the character questions about yourself.

	Not at all	Very slightly	A little	Moderately	Quite a bit	Extremely
1: How similar do you feel to **Person B?**	○	○	○	○	○	○

GAPIM-D

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- Plus random effects
  - σ_α^2: Actor variance (random intercept)
  - σ_β^2: Picture variance
  - σ_ε^2 :error

Group Composition Results

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Partner		
Others		
Dyadic Similarity		
Actor Similarity		
Partner Similarity		
Others Similarity		

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Model Comparisons

Model	SABIC
Additive Model	1188.72
Dyadic Model	1197.74
Parallel Interaction Model	1190.62
FLS Model	1189.65
Fau Model	**1185.94**

Summary of Study 2

- There were dyadic similarity effects for race and gender
- There were effects due to the others—dyadic perceptions of similarity were influenced by the race of the other group members.
- Effects of dyadic similarity in gender and dyadic similarity in race were present in both studies
  - The sizes of these effects varied across studies:
    Study 2 > Study 1

General Conclusions

- There was some evidence for non-additive effects of race and gender composition, but the specific faultline measures were generally unsuccessful
  - Overlap between the GAPIM parameters and the level of measurement of the outcome variable may be responsible
- Might want to match the Faultline measure to the level of measurement of the outcome.
- Simpler, more intuitive measure of group alignment (correlations) might be better when only two composition variables are involved. With >2 variables more sophisticated methods are needed.

Thank you!

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