A Novel Effect Size Measure for Mediation with a Multicategorical Predictor

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INTRODUCTION

- Numerous effect size measures for mediation face limitations when dealing with a nominal predictor encompassing three or more categories. To tackle this issue, the mediation effect size measure \mathbf{v} was introduced.
- We conducted comprehensive simulation study with various factors in data generation and effect size estimation, and we presented an empirical example to illustrate its usage.

METHODS

- 1. Five factors were manipulated in the simulation study: number of groups in X, sample size per group, effect size of ai paths, size of b path, and effect size of c'i paths; 720 conditions with 10,000 replications for each condition.
- 2. Performance evaluators: bias, standardized bias, mean squared error (MSE), and coverage rate.
- 3. ANOVAs were conducted to study the effects of each factor, followed by post-hoc pairwise comparisons and boxplots.

RESULTS

- The Olkin-Pratt extended method on the sample estimator of υ ($\tilde{\upsilon}_{OPE}$) had the least bias and the lowest mean squared error (MSE). See **Table 1**.
- R-squared methods and unadjusted method had large 2. biases.
- 3. As Figure 1 shows, the adjusted sample estimator was highly influenced by b path size (along with effects of ai paths' effect size, c'i paths' effect size, and number of groups).

FINDINGS & CONCLUSIONS

• We extended the mediation effect size υ to multicategorical predictor mediation models. • The current study showed that υ lacked some desirable properties in this scenario.

• There are couple factors affecting v estimator accuracy: size of b path, small effects in ai paths

• R-squared shrinkage methods could not effectively reduce bias of v estimates Recommendation: Use $v^{\sim}OPE$ for simple mediation models with multicategorical predictors

• Cautionary scenarios that υ may be inappropriate: Large b path (0.39-0.59), small effects in ai paths, small group sizes (n = 10)

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Figure 1: Boxplot of effect of *b* path on bias of $\tilde{\upsilon}$ OPE.

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Table 1: Comparison of sample estimators of u across conditions.

mple Estimator	Bias	Standardized Relative Bias	MSE	Coverage Rate
$ \hat{v} $.02314	.56756	.00430	71.67%
Claudy)	.02191	.64609	.00445	66.62%
Ezekiel)	.02184	.62681	.00439	63.48%
$ ilde{v}$ ($ ilde{v}_{OP}$)	.02103	.65311	.00426	67.43%
Extended $ ilde{v}$ ($ ilde{v}_{OPE}$)	.02080	.65121	.00422	67.64%
att)	.02088	.66614	.00423	67.54%
mith)	.02171	.52229	.00439	66.79%
Walker)	.02204	.64510	.00448	66.44%
ÿ _{Wherry})	.02253	.52666	.00457	64.84%

