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Youth Prevention Programs: A Framework for Conducting Mediation Meta-Analyses

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YOUTH PREVENTION PROGRAMS: A FRAMEWORK FOR CONDUCTING

MEDIATION META-ANALYSES

by

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ABSTRACT

Youth Prevention Programs: A Framework for Conducting Mediation Meta-Analyses

by

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Mediation analysis has surged over the past three decades for prevention and intervention program designs, drawing attention to process-oriented explanations for how programs exert their effects. Mediation analysis is a statistical technique that measures how an independent variable predicts one or more mediating variables, which in turn, predicts a dependent variable. Given the growing number of process-oriented intervention studies, the time has come to comprehensively examine mediation effects to gain a deeper understanding of *how* interventions work. Such an investigation has yet to transpire and there is not an established theoretical nor quantitative framework for measuring mediated effects in a meta-analytic context. As such, this thesis was driven by four research objectives: (1) To create a theoretical and quantitative framework under which to evaluate mediated effects across multiple studies, in order to measure what types of program mediators are associated with the largest effect sizes; (2) to demonstrate an application of this framework based on simulated data; (3) to discuss a real-world

application of this framework across youth violence intervention studies and the limitations that exist in current methodological practices; and (4) to discuss the broader implications of this approach. This framework has the power to identify the most critical actions that practitioners and policymakers can take to prevent specific youth risk behaviors. This is substantively important because this framework can be applied in multiple contexts of research and program evaluation, which may aid in decisions centered on supporting youths' well-being.

(64 pages)

PUBLIC ABSTRACT

Youth Prevention Programs: A Framework for Conducting Mediation Meta-Analyses

Morgan A. Kawamura

Often for prevention program designs, researchers are interested in understanding the processes through which a program impacts a targeted outcome. Mediation analysis assists in identifying not only *how* a program influences an outcome, but also *which* intermediate variables (i.e., mediators) cause the effects between a program and an outcome to occur. Mediation analysis explains *why* a program works, which is useful for program developers in creating effective prevention and intervention-based programs.

To make use of mediation analysis findings for preventive intervention programs, researchers need a comprehensive understanding of the mediators between various programs and outcomes. However, a comprehensive examination into which mediators are most effective has yet to take place. This is likely due to the lack of theoretical and quantitative guidance on conducting a comprehensive comparison study for mediated effects. As such, this work establishes a framework for measuring mediated effects in a comprehensive context. This thesis establishes a framework under which to evaluate mediated effects across multiple studies, demonstrates the application of this framework, and discusses the broader implications of this approach. Identifying the most effective mediators through the proposed approach lends a valuable understanding to practitioners and policymakers about critical actions for preventing a given outcome.

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Above all, I owe recognition to my family, and the best way to acknowledge their boundless support is by dedicating this thesis, and all work accompanying it, to them. First, I dedicate this work to my fiancé, Devin Hansen, who supported me unconditionally through the highs and lows of this period in my life. For holding high expectations of me, pushing me to meet those standards, and still loving me during the times I failed—I dedicate this work to him. I also dedicate this thesis to my patient family, who always believed in my dreams and infinitely surround me with love and support. Their guidance and encouragement bolstered my success throughout this process and for that, I am grateful. To all my people, I love you.

Morgan A. Kawamura

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CHAPTER I

INTRODUCTION

Prevention scientists, among other youth program researchers, are often interested in examining the processes through which prevention and intervention programs exert their effects on risky behavioral outcomes. Over the past few decades, prevention program designs have largely adopted process-oriented approaches, which specify theory-driven causal mechanisms (MacKinnon, Fairchild, & Fritz, 2007). Commonly, mediation analysis is the statistical technique used to understand such mechanisms. In mediation analysis, an independent variable (e.g., intervention program) predicts one or more mediating variables (e.g., social skills), which in turn, predicts a dependent variable (e.g., youth violence; MacKinnon, 2008). The idea that programs provoke change on an outcome through an intermediate construct suggests an underlying causal process taking place between the program and outcome, which provides information about *how* a program exerts its effects. Understanding these mechanisms is critical in leading practitioners and researchers to determine actions that ensure preventive intervention programs successfully employ their effects on targeted behavioral outcomes. In addition to these benefits, at the least, mediation analysis can help reduce the risk that researchers fail to gain insight on how an intervention can be improved.

Given the growing number of process-oriented intervention studies over the past several decades (MacKinnon et al., 2007), it is now time to evaluate the research base with a concentration on theory-driven causal mechanisms in meta-analytic contexts. Meta-analyses integrate and summarize research findings from a body of existing

research (Glass, 1976), providing evidence of overall effects based on previous studies' conclusions. A comprehensive evaluation using meta-analytic techniques is desirable because it allows the examination of aggregate effects across various populations. Until now, meta-analysts evaluated youth intervention programs by comparing program-related effect sizes, lending valuable information about the types of programs with the potential to impact targeted outcomes (e.g., Alford & Derzon, 2012; Gavine, Donnelly, & Williams, 2016). These prior meta-analytic evaluations showed *whether* programs worked but did not show *how* programs worked. To gain a deeper understanding of *how* interventions work, a meta-analytic investigation that evaluates critical program mediators will create a deeper understanding of how interventions work. Identifying important program mediators helps explain intervention effects and reveals the most critical actions prevention efforts can take to ensure intervention programs affect the targeted outcome behavior in the desired manner.

Despite its importance, a meta-analytic investigation into the strongest mediator variables of successful youth prevention programs has yet to emerge and this is likely because no theoretical nor quantitative framework currently exists to quantify mediated effects across studies examining mediated processes. Pressingly, the purpose of this thesis is to specify a framework for measuring mediated effects in a meta-analytic context and is driven by four research objectives: (1) To create a theoretical and quantitative framework to evaluate mediated effects across multiple studies, in order to measure what types of program mediators are associated with the largest effect sizes; (2) to demonstrate an application of this framework based on simulated data; (3) to discuss a real-world

application of this framework across youth violence intervention studies and the limitations that exist in current methodological practices; and (4) to discuss the broader implications of this approach. To facilitate these research objectives, this framework is guided by the following theoretical foundations.

CHAPTER II

THEORETICAL FOUNDATIONS

Traditionally, intervention program designs encompassed “black box” approaches, where programs affected behavioral outcomes without attention to underlying causal mechanisms of *how* they work. In addition to these traditional approaches, process-oriented approaches (i.e., mediation designs) help shed light on the concept that rarely do interventions directly impact behavioral outcomes but rather work *through* intermediate variables. Mediation analysis, the statistical technique for testing this process-oriented approach, is utilized in prevention program research because it provides an explanation of how programs work (Lockhart, MacKinnon, & Ohlrich, 2011; MacKinnon, 2008), in which, an independent variable predicts one or more mediators, which, in turn, predicts the behavioral outcome.

There are two components of the mediation model that determine whether a program is successful in reaching the desired effect, the Action Theory and Conceptual Theory components. The Action Theory represents which elements a program has the power to impact (i.e., which elements of a program are most critical) while the Conceptual Theory determines the part of the process not under direct influence of the program to change (i.e., which mediators are most critical; Chen, 1990). Action Theory Success (ATS) and Conceptual Theory Success (CTS) are achieved when both pathways have significant effect sizes. ATS is an essential condition for a program to be successful and is a necessary precursor for CTS (Chen, 1990). Generally speaking, the strongest mediators are those that have the largest effect sizes in both components of the model

(MacKinnon, Lockhart, Baraldi, & Geldand, 2013). Figure 1 shows the causal pathway of a single mediator path model where α represents the effect from the independent variable to the mediator (Action Theory), β represents the effect from the mediator to the dependent variable or outcome (Conceptual Theory), and *c*` represents the direct effect of the independent variable on the dependent variable while controlling for the mediating variable.

The paths in the single mediator path model are expressed in the form of three regression equations:

$$Y = i_1 + cX + e_1, \tag{1}$$

$$Y = i_2 + c`X + bM + e_2, \text{ and} \tag{2}$$

$$M = i_3 + aX + e_3. \tag{3}$$

In these equations, Y is the dependent variable, i_1, i_2, and i_3 are intercepts, X is the independent variable, M is the mediator, c is the estimate of the total effect, c` is the estimate of the direct effect of the independent variable on the dependent variable adjusted for the mediator, b is the coefficient estimate for the mediator to the dependent

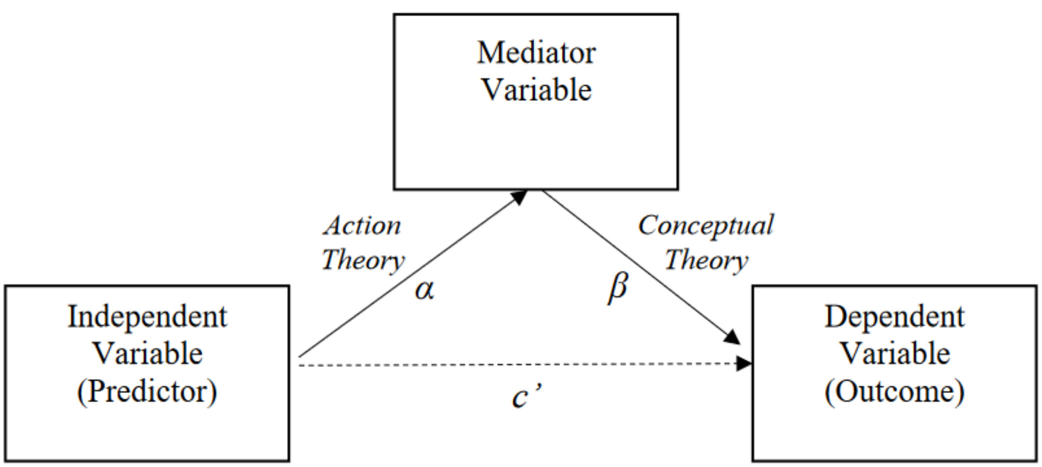

Figure 1. Single mediator path model.

variable adjusted for the independent variable, a is the coefficient estimate for the independent variable to the mediator, and e_1, e_2, and e_3 are residuals (MacKinnon et al., 2007).

Assessing effects of both ATS and CTS separately in a meta-analysis reveals valuable information about which elements of a program are effective for targeting mediators and which mediators are effective for targeting the outcome behavior. However, mediation assessment for program evaluation generally involves estimating a single parameter for the mediated effect by multiplying the *a-path* (α-path, in Figure 1) and *b-path* (β-path, in Figure 1) regression weights. This product of coefficients parameter represents the expected change in the outcome behavior resulting from the mediator, after controlling for the direct effect of the predictor (intervention condition). Determining which mediator types produce the largest global effect sizes (i.e., product of coefficients, in this case) allows meta-analysts to evaluate the most critical mediators that can be targeted for preventing a specific youth risk behavior.

CHAPTER III

QUANTITATIVE FOUNDATIONS

In conjunction with the theoretical foundations contributing to the development of this meta-analytic structure, there are also quantitative foundations that support and guide the proposed framework.

Recommended Coding Procedure

General Procedures

Part of evaluating a meta-analysis is creating a strong coding scheme. Meta-analysts should define their sample, collect their studies, and practice coding protocol using skilled and suggested techniques outlined by Card (2012). Analysts need to also develop a coding interface and manual, as recommended by Wilson (2009), in which, the coding interface refers to the systematic format for coders to collect and record data and the coding manual is a document that provides instructions to accurately and completely extract the appropriate information from the articles. This coding manual is used to train coders to properly extract data from studies and the interface provides a tool for inputting and storing data. Upon the completion of the coder training, coders should practice coding articles until a satisfactory level of agreement between coders is achieved. Once the satisfactory agreement level is reached, coders should be randomly assigned articles to code so that each article is coded more than once by different coders. Intrarater and interrater reliabilities should be assessed using Cohen's κ, for categorical codes, and Pearson's r, for ordinal or numeric codes.

Coding Mediator Types

Categorizing mediators is necessary to determine which *types* of program mediators have the largest effect sizes. Since there is no established classification system to categorize mediators within this specific realm of research, researchers should construct coding schemes based on previous research findings in the literature base and theoretical reasoning. Coding should begin with initial, pre-determined coding categories of mediator types and allow for an evolving and organic process, in which typologies are created or modified as necessary.

Methodological Study Quality

The proposed quantitative framework recommends coders measure the methodological quality of each study's program design and analytic procedures by using a scoring method originally created by Lubans, Foster, and Biddle (2008) and revised by Kawamura and Lockhart (2019). To determine study quality, coders should identify the presence of (1) a theoretical framework, (2) use of an experimental design, (3) use of baseline controls, and (4) established temporal precedence. Temporal precedence is defined as having at least three measurement occasions for the mediator and outcome (MacKinnon, 2008). Coders should also assess how studies account for attrition rates and missing data given that modern approaches for handling missing data (e.g., full-information maximum likelihood) appear to reduce bias in results over traditional approaches (e.g., listwise deletion; Enders, 2010).

Calculation of Effect Sizes

The global mediated effect size represents a single parameter of the mediated effect and will be used to determine the types of program mediators that are associated with the largest mediation effect sizes. The quantitative underpinning of this effect size is detailed in the following sections.

Testing mediation in program evaluation research and prevention science generally involves estimating a single parameter for the mediated effect by multiplying the *a-path* and *b-path* regression weights. This product of coefficients parameter denotes the expected change in the outcome resulting from the mediator after controlling for the direct effect of the predictor variable. Although this statistic is subject to significance testing and evaluation with effect sizes, interpreting results across studies is particularly challenging because statistical approaches often do not include a single mediation parameter, but rather use guidelines to determine if mediation transpired (e.g. causal steps approach; Baron & Kenny, 1986). To make this process feasible in the meta-analytic context, this framework proposes two phases for interpreting and summarizing effect sizes.

First, for both *a* and *b-paths,* regression weights and standard errors should be collected and the product of coefficients (*a*b)* effect should be coded as significant or not. Studies that assess more than one mediator should test each mediation process separately. If original data is available, meta-analysts should use the bias-corrected bootstrap approach to test the significance of mediation results as demonstrated by MacKinnon, Lockwood, and Williams (2004) because this method generally results in

the least bias among common approaches. Although the bias-corrected bootstrap method is the recommended approach, it requires original data and there are often circumstances when researchers are unable to obtain such data. If original data is not available, studies can be re-analyzed with the Monte Carlo method for assessing mediation (MCMAM; MacKinnon et al., 2004), where confidence limits, based on the distribution of the products, are tested to determine if there is evidence that the mediated effect exists (i.e. effect is beyond the limits) or not. Although the bias-corrected bootstrap method is preferred because it produces less bias, the MCMAM outperforms the single-sample Sobel test and may be useful as it only requires the *a* and *b-path* values and standard errors to compute (MacKinnon et al., 2004), which are common in meta-analytic studies. Preacher and Selig (2012) discuss other advantages of the MCMAM approach, including its quick processing time, which is advantageous when using models that take a long time to converge. It is also beneficial when bootstrapping is not feasible, such as in certain situations of multilevel modeling (Preacher & Selig, 2012).

Second, the mediated global effect size should be calculated. Preacher and Kelley (2011) recommend utilizing a standardized effect size to measure the mediated effect of each study called the completely standardized indirect effect. Equation 4 shows the formula for this standardized global effect size, ab_{cs}, which is largely interpretable and comparable across studies:

$$ab_{\mathrm{cs}} = \beta_{\mathrm{MX}}\beta_{\mathrm{YM}} = ab\frac{s_x}{s_y} \tag{4}$$

The ab_{cs} is used to evaluate control against treatment conditions with regards to the difference in the expected increase in the outcome, indirectly through the mediator. The

ab_{cs} is useful in the meta-analytic context because the standardized metric for the effect sizes yields results that are readily interpretable across studies.

Descriptive Statistics

Meta-analysts should perform descriptive statistics on the variables of interest. If appropriate, researchers should evaluate variables with measures of central tendency and frequency distributions. They should also plot raw data and the global effect sizes to visualize data distributions.

Effect Size Weighting, Averaging, and Testing

Effect sizes should undergo a statistical weighting procedure that gives more weight to studies with narrower confidence intervals. Doing so increases precision and accuracy for estimating average effect sizes (Card, 2012). Effect sizes should be weighted by the inverse of their respective studies' squared standard error ($1/SE^2$). Analysts should then calculate weighted mean effect sizes by taking the ratio of the sum of each study's weighted effect size to the sum of the study weights. Researchers can then generate confidence intervals of the weighted average effect size to test the precision of the measure.

Evaluating Publication Bias

Researchers should take multiple steps to reduce the potential for publication bias. Funnel plots, as suggested by Light and Pillemer (1984), evaluate bias from sample size

and Spearman's rank correlation test analyze asymmetry. To determine the extent of publication bias, the trim and fill method (Duval & Tweedie, 2000) can be used for each study before being compared to the initial results. Finally, researchers should use multiple regression to test publication bias from journal ranking and/or published versus non-published results.

Final Mediation Meta-Analysis

To determine what types of program mediators are associated with the largest effect sizes, it is advantageous to use a univariate mixed effects meta-analysis, in which, mediator type predicts the global mediated effect size. In real world contexts, random effects models are chosen when primary studies are conducted by different researchers in different contexts and thus, studies are likely to vary from each other. Mixed effects models extend the random effects models to include study-level characteristics (e.g., fixed effects, like program quality) as predictors (Cheung, 2015a). In this framework, the mediator type is a study-level characteristic, suggesting a mixed effects model is most appropriate.

The univariate mixed effects model with one predictor is represented by the following formula:

$$y_i = x_i^T \beta_R + u_i + e_i, \tag{5}$$

where y_i is the outcome, β_R is a vector of regression coefficients including the intercept, τ^2=var(u_i) is the residual heterogeneity variance, e_i is the error term, and lastly, x_i is a vector of moderators that predict the outcome (Cheung, 2015b). The predictors are

termed moderators in the meta-analytic literature because they moderate the strength of the effect at the study level.

Before interpreting the coefficients of the model, the homogeneity of effect sizes should be assessed. Commonly, the Q statistic is used but may not be a reliable indicator of the degree of heterogeneity due to its sensitivity to sample size (Cheung, 2015a). Instead, τ^2 may be used to measure heterogeneity of effect sizes, but with a major limitation; it largely depends on the types of effect size, meaning, a τ^2 statistic for a correlation coefficient means something different than for a mean difference coefficient (Cheung, 2015a). Higgins and Thompson (2002) suggest three indices that measure heterogeneity of effect sizes that are not dependent on the types of effect size nor number of studies: H, R, and I^2. The I^2 statistic is the most common of the three for measuring the proportion of effect size variance that is due to between-study heterogeneity. When the I^2 is high (> 75%), this suggests effect sizes are relatively homogenous and studies do not represent random sampling variation around a single estimate. Under this condition, moderators, or predictors, are appropriate to add to the model to account for the underlying difference between studies.

CHAPTER IV

DEMONSTRATION

Data Generation

Model Selection

Data for this demonstration were generated by Monte Carlo simulation via M*plus* (Muthén & Muthén, 1998-2017). Figure 2 presents the population model, named in accordance with common labeling schemes in the mediation literature. A three-mediator model with one predictor and one criterion was chosen. The predictor variable, X, was simulated as a binary variable and the criterion, Y, as a continuous variable. The three mediators, M1, M2, and M3, were generated as continuous variables.

The *a-paths* linking X to the three mediators M1, M2, and M3 are represented by α_1, α_2, and α_3, respectively. Whereas, the *b-paths* linking M1, M2, and M3 to Y are

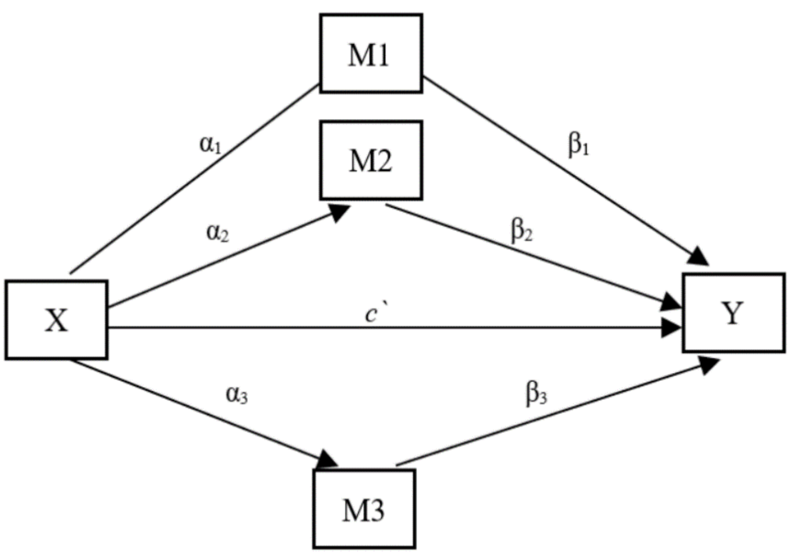

Figure 2. Three-mediator model.

represented by β_1, β_2, and β_3, respectively. The direct effect of X on Y, while controlling for each mediating variable, is represented by c`.

Population Values

Population values and covariance algebra were based on work by MacKinnon (2008) and Thoemmes, MacKinnon, and Reiser (2010) in which, for demonstration purposes, the first mediator was set to produce small effect sizes, the second mediator was set to produce medium effect sizes, and the third mediator was set to produce large effect sizes in both the Action Theory (α) and Conceptual Theory (β) components of the model. The direct effect, *c'*, was simulated to produce a small effect, similarly to the α_1 path coefficient. For clarification and simplicity purposes in the demonstration, intercept terms were set to zero in the simulation. Notably, full Monte Carlo simulation syntax can be found in Appendix A.

First, Cohen's (1988) R^2 (explained variance in the dependent variable) was used to generate path coefficients where the residual variances of the outcome variables were all fixed so that the total variance of the variables summed to 1 (Thoemmes et al., 2010). The independent variable, X, was set as a binary variable with an even split (proportions of possible values of the binary variable were 50% and 50%). Therefore, the variance of X was equal to:

$$Var(X) = .5^2 = .25. \tag{6}$$

The variance of each mediator was reliant on the relationship from X to M_i and the residual term (Thoemmes et al., 2010). R^2 of α_1 and β_1 were set to 2% (small effect), α_2 and β_2 were set to 13% (medium effect), and α_3 and β_3 were set to 26% (large effect).

Thoemmes and colleagues (2010) suggest solving for the variance by substituting known values into the following formula:

$$Var(Mi) = 1 - R^2. \tag{7}$$

Thus, calculating the residual variance for each mediator produces the following values:

$$Var(M1) = 1 - 0.02 = 0.98,$$

$$Var(M2) = 1 - 0.13 = 0.87, \text{and}$$

$$Var(M3) = 1 - 0.26 = 0.74.$$

Similarly, the variance of the dependent variable, Y, is reliant on the relationship between X to Y, each M to Y, and each covariance between X and M (Thoemmes et al., 2010), and was calculated with the following formula:

$$Var(Y) = \beta_{M1}^2 Var(M1) + \beta_{M2}^2 Var(M2) + \beta_{M3}^2 Var(M3) + Var(e). \tag{8}$$

Since all continuous variable variances were set equal to 1, the following formula was used to solve for Var(*e*), producing a value of .5907.

$$1 = \beta_{M1}^2 \times 1 + \beta_{M2}^2 \times 1 + \beta_{M3}^2 \times 1 + Var(e) \tag{9}$$

$$1 = .0196 \times 1 + .1296 \times 1 + .2601 \times 1 + Var(e) = .4093 + Var(e).$$

When the β coefficients (defined and calculated below) and the Var(*e*) values are inserted into Formula 8, the variance of Y was solved as follows:

$$Var(Y) = .0196 \times .98 + .1296 \times .87 + .2601 \times .74 + .5907 = .915.$$

After the variance components were calculated, the unstandardized path coefficients for the *a-paths* were calculated based on the following formula:

$$\alpha_i = \frac{\sqrt{1 - Var(e_{M_i})}}{\sqrt{Var(X)}} \tag{10}$$

Calculating the *a-paths* for each of the three mediators produces the following unstandardized path coefficients:

$$\alpha_1 = \frac{\sqrt{1 - .98}}{\sqrt{.25}} = .283$$

$$\alpha_2 = \frac{\sqrt{1 - .87}}{\sqrt{.25}} = .721$$

$$\alpha_1 = \frac{\sqrt{1 - .74}}{\sqrt{.25}} = 1.02.$$

The unstandardized path coefficients for the *b-paths* were calculated from the following formula:

$$\beta_i = \sqrt{Var(e_i)} \tag{11}$$

Calculating the *b-paths* for each of the three mediators produced the following unstandardized path coefficients:

$$\beta_i = \sqrt{0.02} = 0.14$$

$$\beta_i = \sqrt{0.13} = 0.36$$

$$\beta_i = \sqrt{0.26} = 0.51.$$

After the model parameters were set, 100 replications of 200 observations were simulated. Figure 3 presents the simulated parameters for the selected model.

Substantive Example

To make the application of this meta-analytic framework more concrete, it is useful to apply it to a substantive example. Accordingly, the following scenario acts as the conceptual placeholder for the simulated data discussed above. The 100 replications

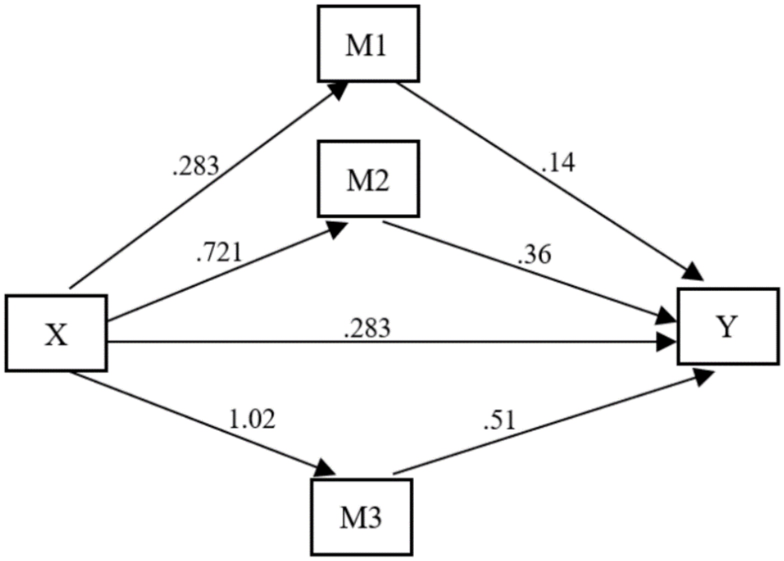

Figure 3. Population parameters for the selected model.

of 200 observations generated in the Monte Carlo simulation via M*plus* represent 100 studies with 200 youth participants in each. These studies all represent program evaluations of youth intervention programs targeting one of the top five leading causes of death for youth in the U.S. (Centers for Disease Control and Prevention [CDC], 2016), youth violence, which serves as the outcome risk behavior of interest. The independent variable, X, represents the intervention program (0 = control condition, 1 = intervention condition).

The three mediators generated, M1, M2, and M3 represent mediator *types*, which had the data been real, should be constructed from coding schemes based on previous research findings and theoretical reasoning as discussed in the quantitative framework section of this article. Before the final analysis, meta-analysts and coders would review every mediator studied across all 100 studies and classify mediator type using a systematic coding scheme. The artificial mediators used for this substantive example are

interpersonal skills, cognitive abilities, and beliefs, which were established based on their positive contributions in the prevention program evidence base (Kawamura & Lockhart, 2019). These mediators represent continuous scores on youths' interpersonal skills (i.e., improving social skills, communication, relationships), cognitive abilities (i.e., empathy, coping, behavioral intentions), and beliefs (i.e., attitudes, norms, expectancies). Figure 4 shows the mediator model with the substantive variables in lieu of the variable labeling schemes.

Analysis

Following simulation procedures in M*plus*, all data replications were imported and combined using RStudio (RStudio, 2016) procedures. See Appendix B for all R code and outlined notes regarding effect size calculations, descriptive statistics evaluations, and final mediation meta-analysis procedures.

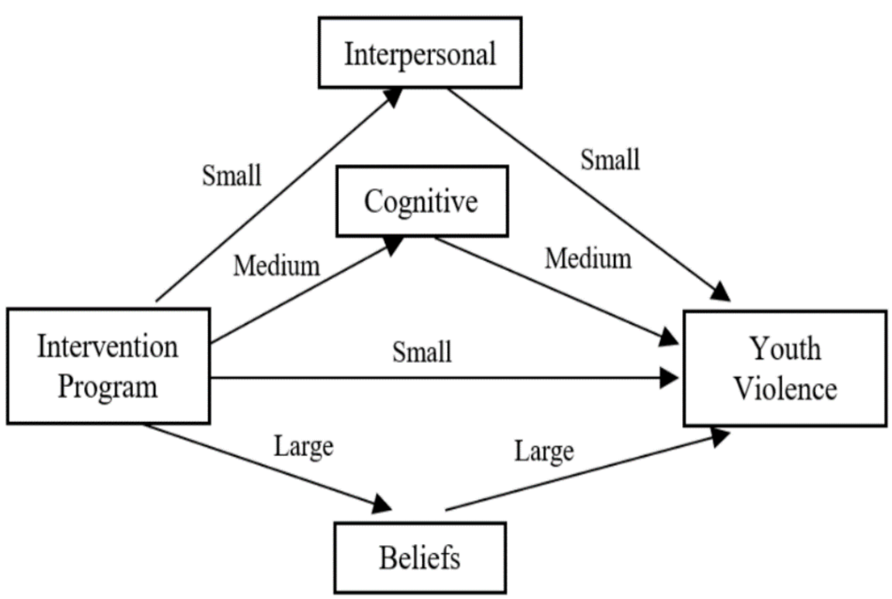

Figure 4. Substantive example of mediator model.

Calculate Effect Sizes

Based on the quantitative foundations of the established framework, global mediated effect sizes were calculated to answer the research question: What types of program mediators are associated with the largest mediation effect sizes?

The established framework recommends two phases for interpreting and summarizing effect sizes: (1) determining whether the product of coefficients ($a*b$) is significant, and (2) calculating the effect sizes. Although the bias-corrected bootstrap approach (MacKinnon et al., 2004) is the least biased among common approaches for determining mediated effect significance, it requires original data, and this is often not possible in meta-analytic research for mediated effects due to the lack of reporting guidelines. Therefore, for demonstration purposes, the Monte Carlo method for assessing mediation (MCMAM; MacKinnon et al., 2004) was performed to test whether the mediated effect occurred by chance (i.e., the effect was beyond the limits). The MCMAM estimates, tested for each mediator separately (i.e., a_1*b_1, a_2*b_2, and a_3*b_3), all fell within the 95% confidence interval, suggesting the mediated effects for each of the three mediators did not occur by chance, across all 100 studies. Next, the standardized global effect size, ab_{cs}, as recommended by Preacher and Kelley (2011), was calculated for each of the three mediators (i.e., interpersonal skills, cognitive ability, and beliefs) using Formula 4 from the quantitative foundations section of this article. This global effect size was used for the final analysis.

Descriptive Statistics

Prior to final analysis, descriptive statistics were performed on all raw variables,

across all 100 studies. Frequency distributions were performed on categorical variables, namely the intervention program. Measures of central tendency (i.e., means, standard deviations, medians, minimum values, maximum values, range, skewness, kurtosis, and standard errors) were computed for continuous variables in the analysis: Interpersonal skills, cognitive ability, beliefs, and youth violence. In addition to frequency distributions and measures of central tendency, scatterplots and histograms were plotted to assess normality. All descriptive statistics and plotting show evidence of variable normality.

In addition to plotting raw data, the global effect sizes were plotted to visualize data distributions. As expected, based on population parameters set during data simulation, the global effect size for the first type of mediator, interpersonal skills, showed the lowest global effect size while the third mediator type, beliefs, showed the highest. The second mediator type, cognitive ability, had an effect size between the two. Figure 5 shows a boxplot of these plotted global effect sizes. This pattern is expected to

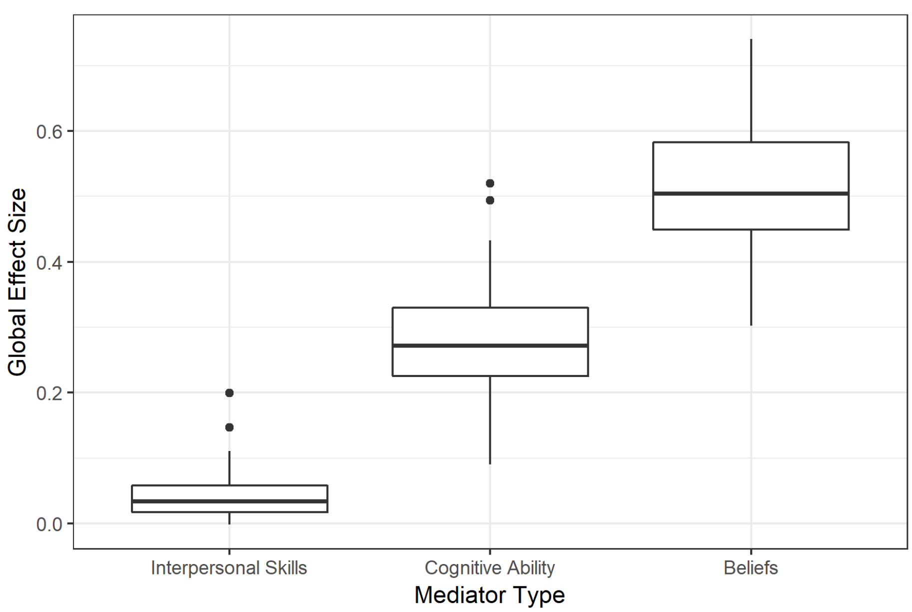

Figure 5. Global effect sizes by mediator type.

appear in the final mediation meta-analysis with regards to predicting which mediator type is associated with the largest effect size.

Effect Size Weighting, Averaging, and Testing

Because the simulated data were based on the same sample size of 200 participants from each of the respective 100 studies, it is not necessary to weight each of the calculated effect sizes prior to final analyses. This is a crucial step for meta-analysts with varying sample sizes, however, because results from studies with larger sample sizes may be influenced by sampling error and should be given more emphasis in the analysis to increase the precision and accuracy for estimating effect sizes (Card, 2012).

Evaluating Publication Bias

This step was also not needed due to the nature of the simulated data. However, this does not mitigate the importance of this step in the quantitative and theoretical framework of this approach. Meta-analysts should take multiple steps to reduce the potential for publication bias, as discussed in the quantitative foundations of this article, including methods suggested by Light and Pillemer (1984) and Duval and Tweedie (2000), for example.

Final Mediation Meta-Analysis

To determine what types of program mediators are associated with the largest effect sizes, a univariate mixed effects model was estimated in RStudio using the “metaphor” package (Viechtbauer, 2010). This package provides functions for

performing univariate and multivariate meta-analyses for fixed-, random-, and mixed-effects models. Within each study (i.e., replication), each mediator was dummy-coded according to mediator type (0 = *interpersonal skills*, 1 = *cognitive abilities*, or 2 = *beliefs*). The interpersonal skills mediator was selected as the reference group because it was expected to have the lowest effect sizes of the three types of mediators (see Figure 5). Mediator type was then used to predict the global mediated effect size.

To determine the amount of heterogeneity in the true beta estimates, the I^2 statistic was analyzed as recommended by Higgins and Thompson (2002). The I^2 indicates that, with mediator type as a moderator in the mixed effects model, only 10% of the total variation in the effect sizes is due to between-study differences. R^2 is used to measure the degree of prediction of the moderators. In this model, mediator type explained 99.58% of the variance in the global effect sizes according to the R^2 statistic. The model coefficients indicate that the third mediator, beliefs, predicted the highest global effect size, followed by the second mediator, cognitive ability. The reference mediator, interpersonal skills, predicted the lowest global effect size, as expected based on the simulated parameters. The (unstandardized) regression coefficients, standard errors, *z*-values, 95% confidence intervals for the estimates, and *p*-values for the univariate mixed effects model are found in Table 1.

Table 1

Univariate Mixed Effects Model

Predictor	β Estimate	Standard error (SE)	*z*-value	CI (Lower)	CI (Upper)	*p*-value
Intercept	.026	.003	9.936	.020	.033	< .0001
Cognitive ability	.227	.008	29.114	.211	.242	< .0001
Beliefs	.470	.011	44.829	.450	.491	< .0001

Note. Reference mediator (intercept) is interpersonal skills. 95% confidence intervals.

CHAPTER V

DISCUSSION

Real-World Applications

In real-world applications, evaluating program-mediated effects across studies is useful, as argued by this article, because it allows researchers to identify critical program mediators that help explain intervention effects and reveals the most important actions prevention efforts can take to ensure programs affect the targeted outcome behaviors in the desired manner. This article provides a theoretical and quantitative structure for evaluating these types of mediated effects across multiple studies, in order to identify and understand the types of program mediators that are associated with the largest effect sizes. Further, this article demonstrates an application of this framework using simulated data; however, it may also be applied in real-world contexts for programs that evaluate mediated pathways, should the studies report enough information to properly calculate a global effect size.

Kawamura and Lockhart (2019) endeavored to meta-analytically assess mediated pathways in a real-world context, among youth violence prevention programs spanning three decades, using the proposed theoretical and quantitative framework outlined by this article. Because youth violence is a world-wide and national issue with significant consequences impacting overall disability, health, and early death (World Health Organization, 2018), mitigating and discouraging violence-related outcomes has led prevention program efforts to design programs aimed at reducing violent behaviors. The

authors' objective to perform a meta-analysis on the mediated effects across prevention programs targeting youth violence proved unsuccessful due to the limitations in current methodological practices. As such, their review took more of a narrative approach to comprehensively investigate the types of mediators utilized across preventive intervention programs targeting youth violence, across multi-component interventions and targets. They identified and defined five mediator types practiced in this literature base: (1) beliefs, (2) interpersonal, (3) cognitive, (4) consequences, and (5) parental change. Three of these typologies, beliefs, interpersonal, and cognitive mediator types, were used as part of the substantive placeholder in the simulated demonstration of this article.

A key limitation across current methodological practices is that global mediated effect sizes are often unattainable due to the lack of statistical information being reported amongst program evaluation studies. This inability to attain and calculate an appropriate effect size may be due to the varying methods for conducting mediation analysis (e.g., path analysis, growth curve models, ANOVAs) that are difficult to compare to one another, and the clear absence of reporting guidelines and standards. In their review, Kawamura and Lockhart (under review) found that some studies reported unstandardized beta coefficients but did not report corresponding standard errors, making it challenging to estimate standardized beta estimates that are comparable across studies. Program evaluation studies ideally should report standardized beta coefficients (if available), unstandardized beta coefficients, and the standard errors of the unstandardized estimates, to ensure meta-analysts and review researchers can properly synthesize research results in

a methodologically appropriate way. At the very least, program evaluation studies testing mediating pathways should report correlation tables and/or coefficients between variables, so that global mediated effect sizes can be computed manually and compared across studies. For instance, the ab_{cs} completely standardized indirect effect, which is the global effect size presented in this framework, can be calculated by multiplying the *a-path* and the *b-path* together. The *a-path* is calculated as correlation between the program and the mediator, whereas the *b-path* is calculated with a partial correlation between the mediator and the outcome because it controls for the direct effect of the program on the outcome (*c'-path*) as well as the effect of the program on the mediator (*a-path*) (MacKinnon, 2008). The partial correlation for the *b-path* is outlined in the following formula (MacKinnon, 2008):

$$r_{YM.X} = \frac{r_{XY} - r_{MY} r_{XM}}{\sqrt{(1-r_{XY}^2)(1-r_{XM}^2)}} \quad (12)$$

Therefore, even the correlation coefficients alone allow computations of both *a*- and *b-path* effect sizes and, ultimately, the global effect size.

Limitations and Future Directions

The central objectives of this article were (1) to create a theoretical and quantitative framework to evaluate mediated effects across multiple studies, in order to measure what types of program mediators are associated with the largest effect sizes; (2) to demonstrate an application of this framework based on simulated data; (3) to discuss a real-world application of this framework across youth violence intervention studies and the limitations that exist in current methodological practices; and (4) to discuss the

broader implications of this approach. This article concludes with a discussion about the limitations and future directions of this approach, as well as a discussion of the broader implications of this meta-analytic framework.

The proposed framework is limited as it does not incorporate a developmentally responsive framework for testing *when* mediators matter most. Such a framework for testing mediated effects as youth experience important developmental shifts (e.g., ecological changes, educational shifts, normative time points, and so forth) reveals critical life points for which practitioners and policymakers have the best chance at preventing certain risk behaviors. As such, future work should focus on how mediation effect sizes are developmentally time-linked to determine the optimal time to implement a prevention or intervention program for a given group of adolescents. Additionally, the proposed framework does not account for the measurement of mediators across multiple time points, which is a limitation to longitudinal program evaluation studies that often span multiple years.

A second limitation of the proposed framework is it does not investigate *under which conditions* mediators matter most. Future work should focus on meta-analytically assessing variation in mediated effects by identifying and testing moderators that produce differences in the Action Theory and Conceptual Theory components, revealing which, if any, part of the mediation model succeeds and for whom. Testing variation in these components' effect sizes might be done with a moderated mediation technique (Baron & Kenny, 1986) where the strength of either the Action or Conceptual Theory is conditional on the moderator. It is important to understand how diverse sources of variation (i.e.,

moderators) predict Action Theory Success and Conceptual Theory Success because it reveals for whom interventions work and why.

Broader Impacts and Implications

Mediation models are often studied in individual-sample tests of program effects whereas the proposed framework contributes to program evaluation theory by offering an approach to meta-analytically investigating these mediation models. This approach summarizes mediated effects by introducing a process-based, theoretical model into the meta-analytic evidence base. This framework has the potential to advance not only prevention science and program evaluation theory but other areas of health research and prevention because it specifies a meta-analytic framework applicable to program evaluation studies that test mediating pathways.

This framework serves as a building block to answer the first of many important questions when it comes to synthesizing and summarizing mediated effects across program evaluation studies. This article gives researchers a structured guide for uncovering the types of program mediators associated with the largest effect sizes and bolsters suggestions for advancing the novel mediation meta-analytic evidence base. Future research recommendations will lead to answering critical meta-analytic research questions, such as, *when* do mediators matter most or *under what conditions* do mediators matter most? These types of questions are imperative to fully understanding what truly occurs in the so called “black box” of program evaluation research.

Determining what types of program mediators are associated with the largest

effect sizes has the power to expose the most critical actions that practitioners and policymakers can make to prevent specific youth risk behaviors or outcomes. By creating more effective programs, risky outcomes can be properly targeted and confronted. This is substantively important because this framework can be applied in multiple contexts of research and program evaluation, which aids in decisions centered around supporting youths' well-being and informs programs on what works for preventing or intervening youth risk outcomes.

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APPENDICES

Appendix A

Monte Carlo Simulation Syntax

```
TITLE: Mediation Meta-Analysis Data Generation
 Model with 3 mediators, 1 independent, 1dependent

MONTECARLO:
 NAMES ARE X M1-M3 Y;
 CUTPOINTS = x(0);
 NOBSERVATIONS = 200;
 NREPS = 100;
 SEED = 84321;
 REPSAVE = ALL;
 SAVE = rep*.dat;

MODEL POPULATION:
[X @ 0];
X @ .25;
[M1-M3 @ 0];
M1 @ .98;
M2 @ .87;
M3 @ .74;
[Y @ 0];
y @ .915;
M1 ON X @ .283 (a1);
M2 ON X @ .721 (a2);
M3 ON X @ 1.02 (a3);
Y ON M1 @ .14 (b1);
Y ON M2 @ .36 (b2);
Y ON M3 @ .51 (b3);
Y ON X @ .283 (cpri);

MODEL:
M1 ON X * .283 (a1);
M2 ON X * .721 (a2);
M3 ON X * 1.02 (a3);
Y ON M1 * .14 (b1);
Y ON M2 * .36 (b2);
Y ON M3 * .51 (b3);
Y ON X * .283 (cpri);

MODEL INDIRECT:
Y IND X;

Output:tech9;
```

Appendix B

R Code

I. LOAD PACKAGES

```
library(tidyverse)
library(pander)
library(magrittr)
library(purrr)
library(broom)
library(haven)
library(lavaan)
library(MBESS)
library(ltm)
library(stargazer)
library(furniture)
library(psych)
library(ggm)
library(semTools)
library(metafor)
library(ggplot2)
library(readbulk)
```

II. LOAD DATA

Import, Save, and Combine Data from MPlus

```
data_raw_nest <- data.frame(REP = paste0("rep", 1:100)) %>%
  dplyr::mutate(file = paste0("mplus_datasets/", REP, ".dat")) %>%
  dplyr::mutate(data = map(file,
                           read.table,
                           header = FALSE,
                           col.names = c("M1", "M2", "M3", "Y", "X")))
%>%
  dplyr::select(-file)
```

Unnest data

```
data_full <- data_raw_nest %>%
  unnest(data) %>%
  dplyr::select(REP, X, M1, M2, M3, Y)
```

Open/View Data

```
head(data_full) %>% pander::pander(caption = "First Few Lines of Full D
ataset")
```

First Few Lines of Full Dataset

REP	X	M1	M2	M3	Y
rep1	0	0.9735	0.4718	-0.4761	-0.3251
rep1	1	-0.618	2.373	1.303	0.9478
rep1	1	0.4091	2.046	0.4823	1.41
rep1	0	0.2071	-1.97	-1.404	-2.529
rep1	1	0.7757	0.9363	0.1537	1.163
rep1	1	0.9474	2.211	1.773	2.403

III. MEDIATION MODEL

Full Mediation Model All 100 replications combined

a) Defining the Mediation Model

```
mediation_model <- '
    Y ~ b1 * M1 + b2 * M2 + b3 * M3 + c * X
    M1 ~ a1 * X
    M2 ~ a2 * X
    M3 ~ a3 * X
    indirect1 := a1 * b1
    indirect2 := a2 * b2
    indirect3 := a3 * b3
    total     := c + (a1 * b1) + (a2 * b2) + (a3 * b3)
    M1 ~~ M2
    M2 ~~ M3
    M1 ~~ M3
'
```

b) Fitting the Model

To all data at once - To Check Simulated Parameters

```
fit <- sem(model = mediation_model, data = data_full)
summary(fit, rsquare=TRUE, fit.measures = TRUE)

## lavaan 0.6-2 ended normally after 24 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         14
##
##   Number of observations                         20000
##
##   Estimator                                         ML
```

```
##   Model Fit Test Statistic                       0.000
##   Degrees of freedom                                 0
##   Minimum Function Value               0.0000000000000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic            19858.249
##   Degrees of freedom                                10
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    1.000
##   Tucker-Lewis Index (TLI)                       1.000
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -108335.732
##   Loglikelihood unrestricted model (H1)     -108335.732
##
##   Number of free parameters                         14
##   Akaike (AIC)                              216699.465
##   Bayesian (BIC)                            216810.114
##   Sample-size adjusted Bayesian (BIC)       216765.622
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.000
##   90 Percent Confidence Interval          0.000  0.000
##   P-value RMSEA <= 0.05                             NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.000
##
## Parameter Estimates:
##
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##   Standard Errors                             Standard
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Y ~
##     M1        (b1)    0.139    0.007   20.146    0.000
##     M2        (b2)    0.368    0.007   50.273    0.000
##     M3        (b3)    0.512    0.008   64.753    0.000
##     X          (c)    0.288    0.017   17.107    0.000
```

```
##   M1 ~
##     X         (a1)    0.290    0.014   20.690    0.000


##   M2 ~
##     X         (a2)    0.746    0.013   56.535    0.000
##   M3 ~
##     X         (a3)    1.010    0.012   82.672    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .M1 ~~
##    .M2                0.013    0.007    2.051    0.040
##  .M2 ~~
##    .M3                0.009    0.006    1.505    0.132
##  .M1 ~~
##    .M3                0.002    0.006    0.325    0.745
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .Y                 0.932    0.009  100.000    0.000
##    .M1                0.983    0.010  100.000    0.000
##    .M2                0.871    0.009  100.000    0.000
##    .M3                0.746    0.007  100.000    0.000
##
## R-Square:
##                    Estimate
##     Y                 0.411
##     M1                0.021
##     M2                0.138
##     M3                0.255
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     indirect1         0.040    0.003   14.434    0.000
##     indirect2         0.274    0.007   37.568    0.000
##     indirect3         0.517    0.010   50.977    0.000
##     total             1.119    0.016   70.245    0.000
```

IV. CREATING FUNCTIONS

a) Fit Statistics

```
fit_mediation <- function(tb){
  sem(model = mediation_model, data = as.data.frame(tb))
}
```

c) Path Estimates

```
extract_paths <- function(mod){
  mod %>% coef %>% as.matrix %>% t() %>% as.tibble()
}
```

d) Global Effect Size

```
global_ES <- function(mod){
  mod@Fit@x %>%
  as.matrix %>%
  t() %>%
  as.data.frame %>%
  dplyr::rename("b1"     = V1,
                "b2"     = V2,
                "b3"     = V3,
                "c"      = V4,
                "a1"     = V5,
                "a2"     = V6,
                "a3"     = V7,
                "M1~~M2" = V8,
                "M2~~M3" = V9,
                "M1~~M3" = V10,
                "Y~~Y"   = V11,
                "M1~~M1" = V12,
                "M2~~M2" = V13,
                "M3~~M3" = V14) %>%
  dplyr::mutate(a1*b1) %>%
  dplyr::mutate(a2*b2) %>%
  dplyr::mutate(a3*b3) %>%
  dplyr::rename("global_1" = 'a1 * b1') %>%
  dplyr::rename("global_2" = 'a2 * b2') %>%
  dplyr::rename("global_3" = 'a3 * b3')
}
```

e) Covariance Matrix

```
extract_cov <- function(mod){
  mod %>% vcov %>% as.matrix %>%
  as.data.frame %>%
  tidyr::gather(key = first,
                value = cov) %>%
  dplyr::mutate(second = rep(c("b1", "b2", "b3",
```

```
                               "c",
                               "a1", "a2", "a3",
                               "M1~~M2", "M2~~M3", "M1~~M3",
                               "Y~~Y",
                               "M1~~M1", "M2~~M2", "M3~~M3"), 14)) %>%
  dplyr::mutate(text = "cov") %>%
  tidyr::unite(vars,
               text, first, second) %>%
  dplyr::filter(cov < 1) %>%
  tidyr::spread(key = vars,
                value = cov)
}
```

f) Sampling Variance of Global Effect Sizes

```
sampling_var_global_ES <- function(mod){
  VCOV     = mod %>% lavaan::vcov()
  x        = mod@Fit@x
  JAC      = lavaan:::lavJacobianD(func = mod@Model@def.function, x = x
)
  VCOV.def = JAC %*% VCOV %*% t(JAC) %>%
    diag() %>%
    t() %>%
    data.frame() %>%
    dplyr::rename("var_ES_global_1" = "X1",
                  "var_ES_global_2" = "X2",
                  "var_ES_global_3" = "X3",
                  "var_ES_total"    = "X4")
  return(VCOV.def)
}
```

g) MCMAM

```
MCmam <- function(mod, path){  # path is a number (eg. 1, 2, 3) & mod i
s the column storing the SEM models

    med <- paste0("a", path, "*", "b", path)

    med_name <- paste0("a", path, "_", "b", path)

    name1 <- paste(med_name, "MCmam_est",  sep = "_") %>% quo_name()
    name2 <- paste(med_name, "MCmam_lo95", sep = "_") %>% quo_name()
    name3 <- paste(med_name, "MCmam_up95", sep = "_") %>% quo_name()

    mod %>%
      monteCarloMed(expression = med,
                    object = .,
                    rep = 10000,
                    CI = 95,
```

```
                    outputValues = FALSE,
                    plot = FALSE) %>%
      unlist() %>%
      as.matrix() %>%
      t() %>%
      data.frame() %>%
      dplyr::rename(!!name1 := Point.Estimate,
                    !!name2 := X95..Confidence.Interval1,
                    !!name3 := X95..Confidence.Interval2)
}
```

V. Preparing Dataset For Analysis

Fiting Model to All Simulated Replications **Nesting data into replications (based on the functions created above)**

```
data_nest <- data_full %>%
  dplyr::group_by(REP) %>%
  tidyr::nest() %>%
  dplyr::mutate(model = map(data,  fit_mediation)) %>%
  dplyr::mutate(fit   = map(model, glance)) %>%
  dplyr::mutate(paths = map(model, extract_paths)) %>%
  dplyr::mutate(cov   = map(model, extract_cov)) %>%
  dplyr::mutate(MCmam1 = map(model, MCmam, path = 1))%>%
  dplyr::mutate(MCmam2 = map(model, MCmam, path = 2))%>%
  dplyr::mutate(MCmam3 = map(model, MCmam, path = 3)) %>%
  dplyr::mutate(global_ES = map(model, global_ES)) %>%
  dplyr::mutate(varESg = map(model, sampling_var_global_ES)) %>%
  unnest(fit, paths, MCmam1, MCmam2, MCmam3, global_ES, varESg)
```

ANALYSIS PLAN

VI. CALCULATE EFFECT SIZE

a) MCMAM

MacKinnon, Lockwood, & Williams (2004)

Created in a function above

Unnested in the full dataset

b) Completely Standardized Indirect Effect

Preacher & Kelley (2011)

Calculated in the full model above

Labeled as global_1, global_2, & global_3

VII. DESCRIPTIVE STATISTICS

a) Frequency Distribution

All Categorical Variables

PREDICTOR (X) **function**

```
freq_x <- function(tb){
  data_nest$data[] %>%
  data.frame %>%
  group_by(X) %>%
  summarise(freq=n())
}
```

looped to all replications

```
freqx <- data_full %>%
  dplyr::group_by(REP) %>%
  tidyr::nest() %>%
  dplyr::mutate(freq_x = map(data,  freq_x)) %>%
  unnest(freq_x)

freqx

## # A tibble: 200 x 3
##    REP       X  freq
##    <fct> <dbl> <int>
##  1 rep1      0   103
##  2 rep1      1    97
##  3 rep2      0   103
##  4 rep2      1    97
##  5 rep3      0   103
##  6 rep3      1    97
##  7 rep4      0   103
##  8 rep4      1    97
##  9 rep5      0   103
## 10 rep5      1    97
## # ... with 190 more rows
```

b) Measures of Central Tendency

All Continuous Variables

REMAINDER OF VARIABLES (M1, M2, M3, & Y) **function**

```
cent_tend <- function(tb){
  data_nest$data[] %>%
    data.frame %>%
    dplyr::select(M1, M2, M3, Y) %>%
    psych::describe()
}
```

looped to all replications

```
centtend <- data_full %>%
  dplyr::group_by(REP) %>%
  tidyr::nest() %>%
  dplyr::mutate(cent_tend = map(data,  cent_tend)) %>%
  unnest(cent_tend)

centtend

## # A tibble: 400 x 14
##    REP    vars     n  mean    sd median trimmed   mad   min   max ra
nge
##    <fct> <int> <dbl> <dbl> <dbl>  <dbl>   <dbl> <dbl> <dbl> <dbl> <d
bl>
##  1 rep1      1   200 0.158  1.04  0.145   0.155  1.09 -2.45  2.60  5
.05
##  2 rep1      2   200 0.434  1.03  0.441   0.441  1.10 -2.51  2.66  5
.17
##  3 rep1      3   200 0.416  1.01  0.429   0.432  1.03 -2.53  2.68  5
.21
##  4 rep1      4   200 0.512  1.23  0.467   0.496  1.35 -2.53  3.52  6
.05
##  5 rep2      1   200 0.158  1.04  0.145   0.155  1.09 -2.45  2.60  5
.05
##  6 rep2      2   200 0.434  1.03  0.441   0.441  1.10 -2.51  2.66  5
.17
##  7 rep2      3   200 0.416  1.01  0.429   0.432  1.03 -2.53  2.68  5
.21
##  8 rep2      4   200 0.512  1.23  0.467   0.496  1.35 -2.53  3.52  6
.05
##  9 rep3      1   200 0.158  1.04  0.145   0.155  1.09 -2.45  2.60  5
.05
## 10 rep3      2   200 0.434  1.03  0.441   0.441  1.10 -2.51  2.66  5
.17
```

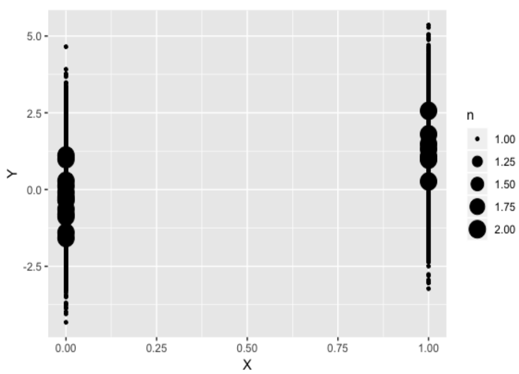
```
## # ... with 390 more rows, and 3 more variables: skew <dbl>,
## #   kurtosis <dbl>, se <dbl>
```

c) Descriptive Plots (Raw Data)

Scatterplots/Histograms (Raw Data)

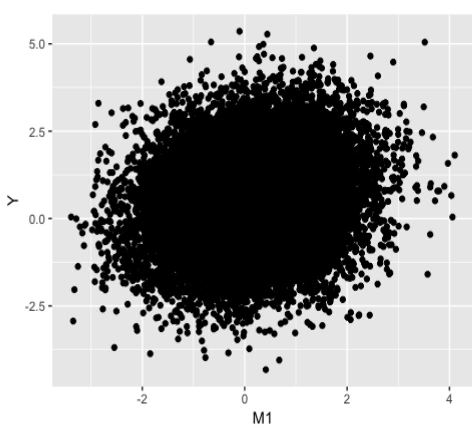
Categorical Variables (X)

```
data_full %>%
  ggplot(aes(x = X,
             y = Y)) +
  geom_count()
```

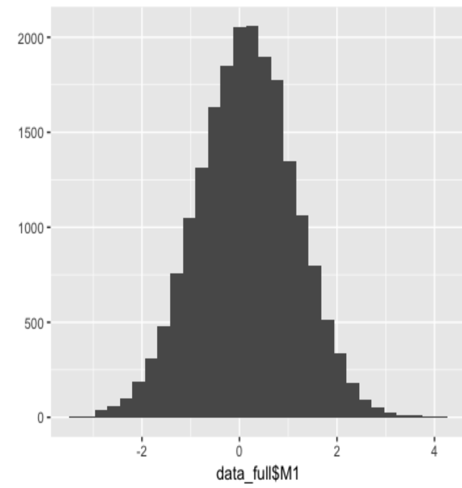


Continuous Variables (M1, M2, M3,Y)

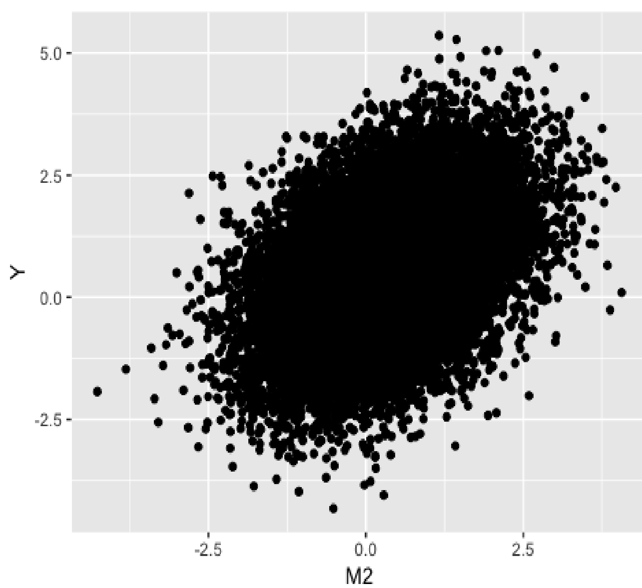
```
data_full %>%
  ggplot(aes(x = M1,
             y = Y)) +
  geom_point()
```



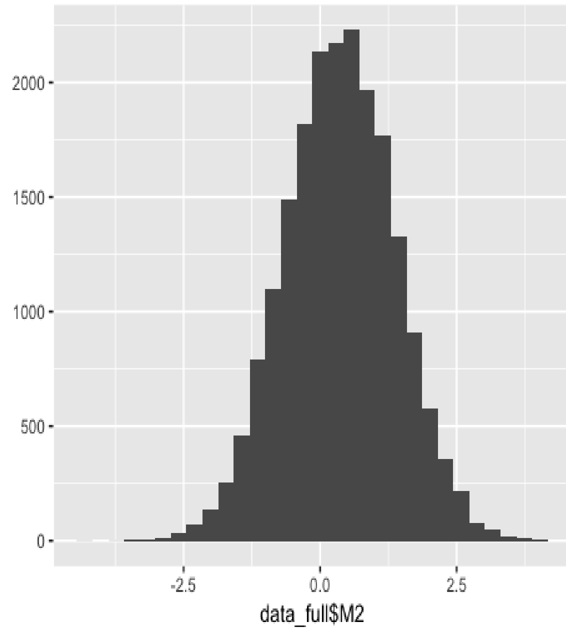

```
qplot(data_full$M1, geom="histogram")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



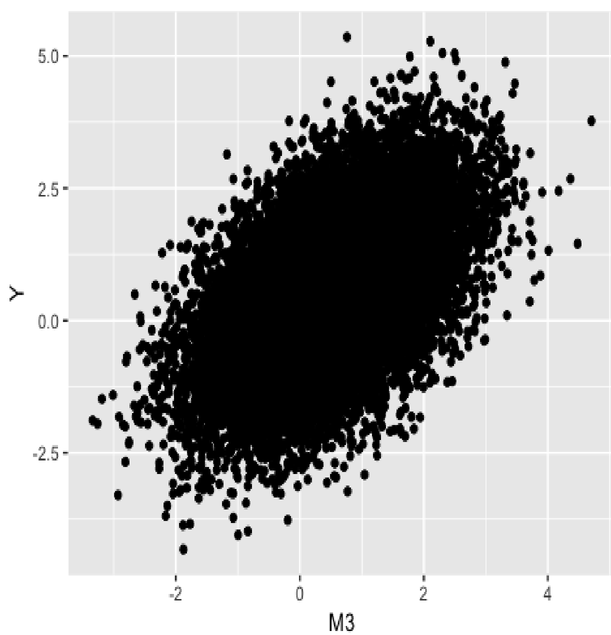

```
data_full %>%
  ggplot(aes(x = M2,
             y = Y)) +
  geom_point()
```



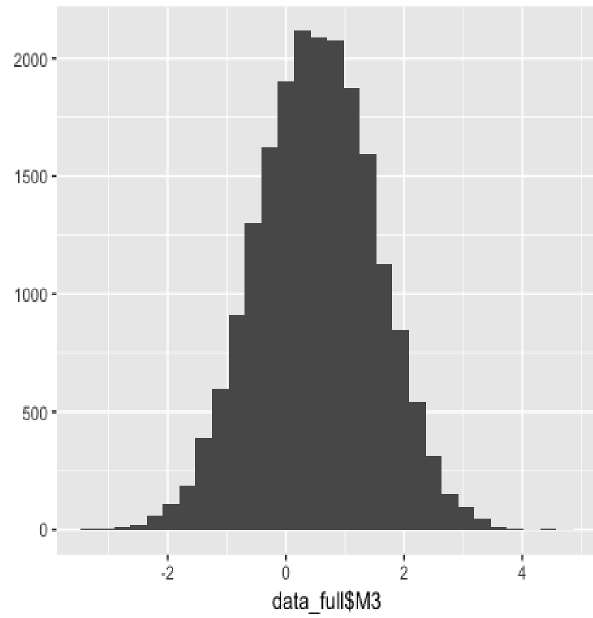

```
qplot(data_full$M2, geom="histogram")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_full %>%
  ggplot(aes(x = M3,
             y = Y)) +
  geom_point()
```



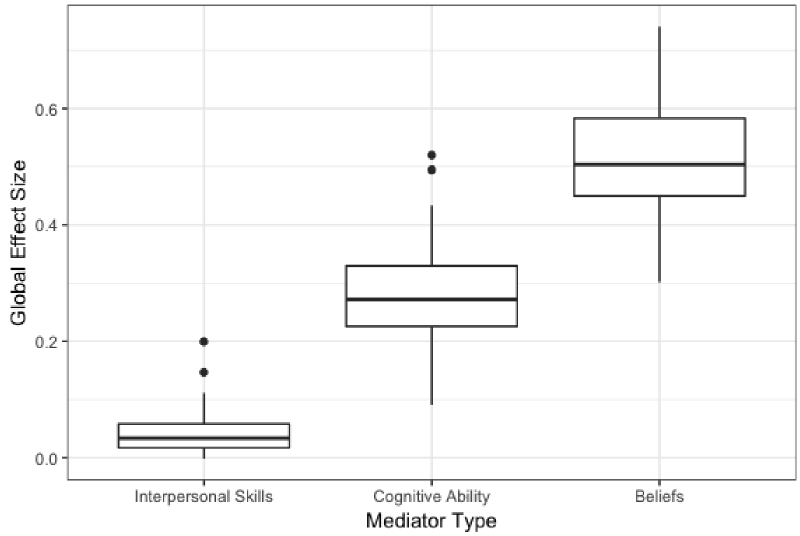

```
qplot(data_full$M3, geom="histogram")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



d) Plots (Global Effect Sizes)

Boxplot

```
data_nest %>%
  tidyr::gather(key = path,
                value = global,
                global_1,
                global_2,
                global_3) %>%
  ggplot(aes(x = path,
             y = global)) +
  geom_boxplot() +
  theme_bw() +
  scale_x_discrete(labels=c("global_1" = "Interpersonal Skills",
                            "global_2" = "Cognitive Ability",
                            "global_3" = "Beliefs")) +
  labs(x = "Mediator Type", y = "Global Effect Size")
```



Global Effect Sizes by Mediator Type

```
ggsave("MedType_GlobEffects.png",
       width = 6,
       height = 4,
       unit = "in")
```

VIII. Univariate Mixed Effects Model

Combining global_1, global_2, and global_3 into 1 vector of length K

```
global <- data_nest %>%
  dplyr::mutate(rep = substr(REP, 4, 6) %>% as.numeric) %>%
  tidyr::gather(key = "variable",
               value = "global",
               starts_with("global")) %>%
  tidyr::separate(col = variable,
                 into = c("mediator", "type")) %>%
  dplyr::select(rep, type, global) %>%
  dplyr::arrange(rep, type)

global

## # A tibble: 300 x 3
##       rep type  global
##     <dbl> <chr>  <dbl>
##  1     1 1     0.0601
##  2     1 2     0.249
##  3     1 3     0.499
##  4     2 1     0.0627
##  5     2 2     0.321
##  6     2 3     0.413
```

```
## 7     3 1     0.0454
## 8     3 2     0.208
## 9     3 3     0.517
## 10    4 1     0.0180
## # ... with 290 more rows
```

Combining var_ES_global_1, var_ES_global_2, and var_ES_global_3 into 1 vector of length K

```
var_ES_glob <- data_nest %>%
  dplyr::mutate(rep = substr(REP, 4, 6) %>% as.numeric) %>%
  tidyr::gather(key = "variable",
                value = "var_ES_global",
                starts_with("var_ES_global")) %>%
  tidyr::separate(col = variable,
                  into = c("var", "ES", "mediator", "type")) %>%
  dplyr::select(rep, type, var_ES_global) %>%
  dplyr::arrange(rep, type)

var_ES_glob
```

```
## # A tibble: 300 x 3
##      rep type  var_ES_global
##    <dbl> <chr>         <dbl>
##  1     1 1          0.00155
##  2     1 2          0.00519
##  3     1 3          0.0104
##  4     2 1          0.00188
##  5     2 2          0.00610
##  6     2 3          0.00809
##  7     3 1          0.000860
##  8     3 2          0.00405
##  9     3 3          0.00965
## 10     4 1          0.000385
## # ... with 290 more rows
```

Joining the global effect sizes and the global variances together and dummy coding the "types" of mediators

```
global1 <- global %>%
  dplyr::inner_join(var_ES_glob,
                    by = c("rep", "type")) %>%
  dplyr::mutate(type1 = case_when(type == 2 ~ 1,
                                  TRUE ~ 0),
                type2 = case_when(type == 3 ~ 1,
                                  TRUE ~ 0))
```

Running the Mixed Effects Model

```
uni_mod_mixed <- metafor::rma.uni(yi = global,
                                 vi = var_ES_global,
                                 mods = ~ type1 + type2,
                                 method = "ML",
                                 data = global1)

summary(uni_mod_mixed)
```

```
##
## Mixed-Effects Model (k = 300; tau^2 estimator: ML)
##
##     logLik   deviance        AIC        BIC       AICc
##   411.1789   327.1607  -814.3578  -799.5427  -814.2222
##
## tau^2 (estimated amount of residual heterogeneity):     0.0001 (SE =
0.0001)
## tau (square root of estimated tau^2 value):             0.0122
## I^2 (residual heterogeneity / unaccounted variability): 10.29%
## H^2 (unaccounted variability / sampling variability):   1.11
## R^2 (amount of heterogeneity accounted for):            99.58%
##
## Test for Residual Heterogeneity:
## QE(df = 297) = 338.3385, p-val = 0.0494
##
## Test of Moderators (coefficient(s) 2:3):
## QM(df = 2) = 2636.0590, p-val < .0001
##
## Model Results:
##
##          estimate      se     zval    pval   ci.lb   ci.ub
## intrcpt    0.0263  0.0028   9.3612  <.0001  0.0208  0.0318  ***
## type1      0.2267  0.0078  29.1704  <.0001  0.2114  0.2419  ***
## type2      0.4700  0.0105  44.8763  <.0001  0.4495  0.4905  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Funnel Plot of mixed effects model

```
funnel(uni_mod_mixed)
```