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# A Structural Equation Modeling Approach Combining Multitrait-Multimethod Designs with Moderated Mediation Analysis

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A STRUCTURAL EQUATION MODELING APPROACH COMBINING

MULTITRAIT-MULTIMETHOD DESIGNS WITH MODERATED

MEDIATION ANALYSIS

by

Kaylee Litson

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# ABSTRACT


A Structural Equation Modeling Approach Combining Multitrait-Multimethod Designs with Moderated Mediation Analysis

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Moderated mediation analysis is a statistical approach used to evaluate the conditional processes among variables. Researchers in clinical and developmental psychology use such methods to determine how and when health behaviors, maladaptive coping, and other mechanisms develop. In simple moderated mediation analysis, an observed exogenous variable $X$ is regressed on an observed intermediary variable $M$, and these two variables are both regressed on an observed endogenous variable $Y$. Further, the relationships among $X$, $M$, and $Y$ may vary as a function of a moderating variable $W$. Generally, moderated mediation analysis is conducted using a single observed variable for exogenous, endogenous, moderating, and intermediary variables. However, one best practice when gathering data is to gather data from multiple methods, and many variables in psychology are measured using multiple methods.

A relative increase in applying moderated mediation analysis and the recommendation of using multimethod designs warranted the creation of the multimethod moderated mediation (M4) model. The performance of the M4 model was examined by applying the model to an extant dataset and conducting a Monte Carlo simulation. The M4 model was applied to a multimethod dataset that included mother and father reports of children's inattention, hyperactivity, oppositional defiant behaviors, and academic impairment. Results showed that the indirect path from hyperactivity to academic impairment through oppositional defiant behavior was significant, but inattention did not significantly moderate the mediated effect. The M4 model was further evaluated using a Monte Carlo simulation design to determine the sample size necessary to have power to detect moderated mediation effects commonly found in applied research. The simulation was additionally used to determine whether method-specificity and model misspecification led to biased moderated mediation results. Results showed that moderated and mediated effects, in the presence of a true multimethod assessment, required using a multimethod measurement structure to accurately evaluate parameter and standard error estimates. When the multimethod structure was not included in the model, results were biased. Further, results found that a sample size of at least $N = 400$ was necessary to detect effect sizes most commonly found among developmental, clinical, and prevention science applications of moderated mediation analysis.

(200 pages)

PUBLIC ABSTRACT

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Kaylee Litson

Researchers who study clinical and developmental psychology are often interested in answering questions such as *how* interventions work, *when* treatment begins to improve health outcomes, or *for whom* treatment has the greatest impact. Answers to these and similar questions impact the general understanding of health and behavior, and can be imperative for effectively implementing intervention and prevention programs. To evaluate such complex relationships among variables, researchers have turned to moderated mediation analysis. Moderated mediation analysis is a statistical tool used to identify the conditional processes among observed or latent variables. However, in developmental and clinical psychology, variables are regularly measured using multiple sources or multiple methods. In fact, best practice recommendations in clinical psychology suggest measuring variables with multiple methods (Achenbach, 2006). The question arises how to use multimethod assessments in statistical analyses such as moderated mediation analysis. The objectives of the present study were to create a multimethod moderated mediation model, apply the model to an extant dataset of child developmental behaviors, and evaluate conditions under which the model performed well using a Monte Carlo simulation study. Results from the application showed that the indirect path from hyperactivity to academic impairment through oppositional defiant behavior was significant but not moderated by inattention. Results from the simulation study indicated that excluding true method effects from a moderated mediation model resulted in unacceptable parameter and standard error bias. These results point to the advantages of using the M4 model to evaluate moderated mediation in the presence of multimethod data.

# DEDICATION

I dedicate this dissertation and the work that led to its completion to my dad, Jim Litson. His unexpected passing in November 2017 was the most heartbreaking moment of my life and has forever changed me. He taught me to work hard, persevere through difficult times, stand up for myself, take responsibility, forgive and move forward, and never give up. More importantly, he taught me that no matter how much hard work lies ahead, take time every day to do small things that bring joy and happiness, whether that meant taking a moment to watch the sunset or enjoying the smell of a cup of coffee. Those little moments have grounded me through my graduate education, and I will forever be grateful for his example and his presence in my life. I dedicate this dissertation to him in remembrance of all the love and support he has given me.

*Kaylee Litson*

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My friends and family have been incredibly patient and supportive as I have continued my Ph.D. education. A very special thank you to my parents, my siblings, and my close friends who were there for me when I celebrated successes and mourned losses. Their support was invaluable to my completion of this work and to staying grounded while pursuing my Ph.D. Another thank you is due to multiple faculty members at USU who have fully supported my graduate career during difficult life moments and have taught me unique ways to approach academic work. I have had opportunities to collaborate and work with scholars who have inspired me to be a better colleague, researcher, and person.

Finally, this research uses data from a dataset provided by Dr. G. Leonard Burns at Washington State University and Dr. Mateu Servera at the University of the Balearic Islands in Spain. I would like to thank both of them, especially Dr. G. Leonard Burns, for providing me this dataset for my application as well as their continual support and collaboration on other projects.

*Kaylee Litson*

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# CHAPTER I

# INTRODUCTION

Researchers in psychology, specifically clinical and developmental psychologists, often seek answers to *how* an intervention works; *when* treatment begins to improve outcomes; and *for whom* a treatment or prevention program is most effective. To answer *how* a treatment works, researchers must identify mechanisms and predictors of outcomes. By identifying the mechanisms through which a predictor influences an outcome, researchers and practitioners can develop applicable prevention or intervention programs (MacKinnon & Dwyer, 1993) to bring about a desired change.

To answer *for whom* or *when* a treatment is most effective, clinical and developmental researchers must identify whether mechanisms and predictors are generalizable across populations or specific to a single population. Prevention scientists use this knowledge to determine for whom prevention or intervention programs are most effective (MacKinnon, Lockhart, Baraldi, & Gelfand, 2013) or to tailor programs to individuals based on individual characteristics (Collins, Murphy, & Bierman, 2004). Understanding the generalizability of processes will lead to better prevention and intervention programs within clinical and developmental psychology. To identify mechanisms and determine for whom the mechanism is most effective, researchers use statistical tools, such as mediation, moderation, or moderated mediation analysis.

In the simplest form of *mediation analysis*, an independent variable, *X*, affects change in the mediating variable, *M*, which affects changes in the dependent variable, *Y* (Baron & Kenny, 1986; MacKinnon, 2008). An example of mediation was shown by

Lúcio et al. (2016) where attention deficit hyperactivity disorder (ADHD) symptoms affected change in stimulus discriminability (the ability to discriminate between, for example, "p" and "q"), which then affected reading ability. Stimulus discriminability was the mechanism through which ADHD symptoms affected reading ability. A primary advantage of mediation analysis is the ability to identify and quantify the mechanism, or the mediator, through which $X$ influences $Y$. The indirect relationship where $X$ influences $M$, which then influences $Y$ is commonly called the indirect or mediated effect (MacKinnon, 2008).

*Moderation* occurs when the relationship between a predictor, $X$, and outcome, $Y$, varies as a function of another variable, $W$. Combined, moderation and mediation analysis are commonly referred to as conditional process models (Hayes, 2013) because the process through which a predictor influences an outcome is conditional on some other variable. Alternatively, such an analysis is called moderated mediation analysis (Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, 2007). *Moderated mediation* analysis is used to determine whether the magnitude of the mediated effect varies as a function of a moderating variable (Edwards & Lambert, 2007; Hayes, 2009; MacKinnon & Fairchild, 2009; Preacher et al., 2007).

Moderated mediation analysis can be used to examine at which levels of the moderator the indirect (or direct) effect varies in magnitude. For example, Lúcio et al. (2016) predicted that the magnitude of the indirect effect from ADHD symptoms to reading ability through stimulus discriminability would vary by age. They evaluated this prediction using moderated mediation analysis. Age did indeed moderate the indirect effect, such that the indirect effect was stronger for younger children than for older children. The researchers explained how these results could be used to implement stimulus discrimination practices (an intervention program) among young children with higher levels of ADHD symptoms (target population) to increase reading ability. This example illustrates how moderated mediation can be used to 1) identify intermediary processes, and 2) detect for whom, or under which conditions, the process is strongest.

Like all statistical methods, moderated mediation analyses have limitations. One such limitation stems directly from the measurement of variables in psychological sciences. Most, if not all, variables in psychology are measured using imperfect methods, sources, or measures, and the method of measurement can impact study results. Consider informant reports of children's levels of social impairment, for example. Mothers who report their child's level of social and academic impairment are likely to differ from teachers who report the same child's level of social and academic impairment. If one wishes to evaluate the relationship between social and academic impairment, it is not only possible, but likely that the method of measurement impacts or biases results (e.g., Podsakoff, MacKenzie, & Podsakoff, 2012; Doty & Glick, 1998). Although mother and teacher report are likely to have some shared consistencies, they may also contain method discrepancies, which can also be termed *method effects*.

Left unattended, method effects impact research results. One problem researchers face is how to best detect and manage systematic method effects so as not to report biased or inaccurate empirical results. Across various fields, the consensus to account for method effects is to measure constructs using multiple *methods* (Achenbach, McConaughy, & Howell, 1987; Achenbach, 2006; Cole, 1987; De Los Reyes & Kazdin, 2005; Hopwood & Bornstein, 2014; Meyer et al., 2001; Morris, Robinson, & Eisenberg, 2006). When first introducing multitrait-multimethod designs, Campbell and Fiske (1959) discussed examples of methods as “paper-and-pencil tests” (p. 85), “peer judgments by students…, [and] scores on a word-association test” (p. 85), “observational methods” (p. 90), “Self Ratings and Inventory scores” (p. 93), “Self and Teammate ratings” (p. 95), and ultimately recommended that “several methods used to measure each trait should be appropriate to the trait as conceptualized” (p. 103). From a more applied perspective, Achenbach and colleagues (1987) described methods as multiple informants, and this idea of informants or raters as methods is present in many studies and theoretical paradigms (e.g., De Los Reyes & Kazdin, 2005; Podsakoff et al., 2012). In Hopwood and Bornstein’s (2014) book, methods include self-attribution tests, performance-based tests, constructive tests (e.g., qualitative responses), behavioral tests, and informant-report tests. These many methods through which data can be gathered require researchers to consider how to use all relevant data in analysis in a way that does not lead to biased results due to method effects.

Despite an emphasis on multimethod measurement in many clinical and developmental settings, multimethod measurement models have not yet been combined with models commonly applied to examine moderated mediation, a statistical approach that is continually gaining traction because of its ability to examine complex relationships among constructs. Currently, no such models exist, which is a disservice for researchers who gather multimethod data and are interested in examining moderated and mediated relationships. By including multiple methods, researchers could determine whether different methods varied together, resulting in consistency across methods (convergent validity; Campbell & Fiske, 1959), or if methods were more discrepant, resulting in method effects.

When researchers gather multimethod data and choose to use a moderated mediation analysis, there are no guidelines for using all available data from methods. To date, there have been no studies examining the effect of method bias on moderated mediation results. It is unclear if method effects truly impact estimates obtained from moderated mediation analysis. It is further unclear how multiple methods could and should be used in conjunction with moderated mediation analysis.

The present project had three objectives. First, create a new statistical method by combining appropriate statistical tools for evaluating multimethod designs with appropriate statistical tools for evaluating moderated mediation analysis. Specifically, the present project combined the so-called correlated-trait correlated-(method–1) (CT-C[*M* – 1]; Eid, 2000; Eid, Lischetzke, Nussbeck, & Trierweiler, 2003) model with a latent variable path analysis approach to moderated mediation (Cheung & Lau, 2017; Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, 2007). Rationale for choosing the CT-C(*M* – 1) measurement model and the latent variable path analysis approach to moderated mediation are discussed in Chapter 2. Second, the present project applied this new multimethod moderated mediation (M4) model to an extant dataset to examine its applicability to real-world data. And finally, the present project examined the performance of the M4 model with a simulation study to determine its usefulness as a statistical tool compared to other moderated mediation approaches.

**Objectives**

1. Create a new model for moderated mediation analysis using an appropriate multimethod measurement structure. This model is called the multimethod moderated mediation (M4) model.
2. Examine the feasibility of the M4 model using an extant dataset to inform how the model works under real data conditions.
3. Examine the performance of the M4 model across various conditions using a Monte Carlo simulation design.

# CHAPTER II

# REVIEW OF THE LITERATURE

As a statistical tool, moderated mediation analysis is relatively new. Since its inception in psychology in 1986 (Baron & Kenny, 1986), moderated mediation analysis has become a tool with which researchers can answer complex questions about the conditional process of a predictor influencing an outcome. For instance, moderated mediation analysis has been used to examine how and under which conditions internalizing symptoms lead to disordered eating behavior (Chardon, Janicke, Carmody, & Dumont-Driscoll, 2015), parental power assertion leads to child antisocial conduct (Kochanska, Barry, Stellern, & O'Bleness, 2009), and sexual minority disparities lead to mental health outcomes (Pakula, Carpiano, Ratner, & Shoveller, 2016).

Applications of this method continue to increase. In 2017 alone, the PsychINFO database showed that researchers in psychological sciences published 293 peer-reviewed publications on moderated mediation analysis compared to 183 publications in 2015, 34 in 2010, and only 2 in 2005. Since this method is a statistical tool with the advantage to uncover complex and intricate relationships among variables, such interest among substantive as well as methodological researchers is expected.

The sea of literature related to moderation, mediation, moderated mediation, and multimethod designs is vast. With the potential to uncover intricate relationships among variables, moderated mediation models can become highly complex. Combined with the proposed latent variable multimethod measurement structure, moderated mediation models can become overwhelmingly complex. To limit the scope of the project and the scope of the literature review, two decisions about the complexity of the approach were made. First, only cross-sectional moderated mediation was addressed. Although longitudinal moderated mediation is necessary for examining causal processes (Baron & Kenny, 1986; MacKinnon, 2008), longitudinal approaches to mediation are statistically more complex and nuanced than cross-sectional approaches (e.g., Selig & Preacher, 2009). Combined with the proposed multimethod moderated mediation approach, a longitudinal design was unfeasible for the scope of the project. Cross-sectional approaches are still examined to determine the potential for causal and conditional pathways in moderated mediation analysis. To further limit the scope of the project, the examined moderating variable was a single continuous moderating variable. Categorical moderating variables, though simpler with regard to latent variable approaches (Lau & Cheung, 2008), were not examined in detail in this project; however, potential extensions and approaches to examining categorical moderators in moderated mediation designs are discussed in Chapter VI.

To address each complexity of mediation, moderation, moderated mediation, and latent variable extensions of all three types of analyses in enough detail, the review of the moderated mediation literature will follow the subsequent structure. First, simple mediation analysis is discussed in the context of path analysis, first with manifest variables then latent variables (including one approach that used a latent multimethod approach, which is relevant for the proposed study). Second, moderation is discussed in the context of regression analysis, first with manifest then with latent variables. Third, moderated mediation analysis is discussed in the context of manifest then latent variables.

**Mediation Analysis**

In simple mediation analysis with only one mediating variable, an independent variable, *X*, affects changes in a mediating variable, *M*, which affects changes in a dependent variable, *Y* (see Figure 1.1). Mathematically, a simple mediation model can be shown with three equations:

$$Y = i_{Y_1} + cX + e_{Y_1} \tag{1}$$

$$Y = i_{Y_2} + c'X + bM + e_{Y_2} \tag{2}$$

$$M = i_M + aX + e_M \tag{3}$$

where *i* indicates the intercept, *a*, *b*, *c*, and $c'$ are the regression paths between variables, *e* indicates the residual error, and *X*, *M*, and *Y* indicate the variables. The original approach to mediation (Baron & Kenny, 1986) used a regression-based method called the *causal steps approach* to evaluate mediated effects. Using this approach required researchers to estimate three equations to determine the total effect *c* from Equation 1, and the mediated effect $a \times b$ in Equations 2 and 3. The causal steps approach required researchers to determine the significance of the $a$ and $b$ pathways, and also show that the

$c'$ pathway compared to the $c$ pathway is closer to zero in order to detect a mediated effect.

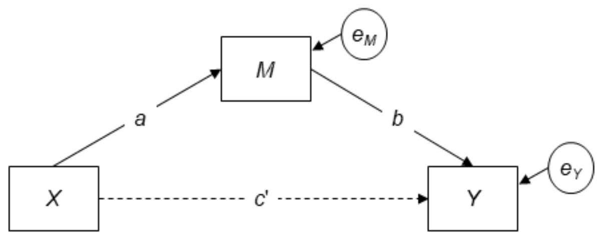


**Figure 1.1**: Simple mediation model

Many researchers have criticized the causal steps approach, showing its lack of power in detecting the mediating effect (Fritz & MacKinnon, 2007; MacKinnon, Coxe, & Baraldi, 2012), and noting its inability to detect mediation if the sign of the mediated effect is opposite of the sign of the direct effect (MacKinnon & Fairchild, 2009). Appropriate to this project, advances in mediation analysis have been developed by way of path analysis (MacKinnon, 2008); latent variable analysis (Bullock, Green, & Ha, 2010; Ledgerwood & Shrout, 2011); and latent variable multimethod analysis (Papa, Litson, Lockhart, Chassin, & Geiser, 2015).

Many advances in mediation analysis have been possible because of the path analysis approach to mediation. Path analysis is an extension of regression analysis that integrates multiple equations into a single statistical model with multiple possible outcome variables. Path analysis allows researchers to specify any reasonable number of exogenous, endogenous, and intermediary variables in a model, and it can be implemented in a single, simultaneous analysis (MacKinnon, 2008). Thus, there is no reason to run three separate models shown in Equations 1 through 3 to examine mediation; only one model need be run. Further, path analysis can easily be depicted using path diagrams, which are visual representations of relationships among variables. These advances in mediation analysis have led to the creation of structurally complex, yet visually interpretable, mediation models.

Generally, path analysis approaches to mediation use manifest variables. In social sciences, it is uncommon that any observed variable is measured without error, yet one assumption of the original Baron and Kenny approach was that “there be no measurement error in the mediator” (1986, pp. 1177). When measurement error is present in mediation analysis, power to detect the mediated effect is attenuated (Fritz, Kenny, & MacKinnon, 2016; Hoyle & Kenny, 1999; MacKinnon et al., 2012). In addition, when measurement error is both present and error terms are correlated (i.e., systematic error), mediation analyses are often biased or inestimable (Pearl, 2012). To correct for measurement error, latent variable approaches have been developed and are frequently used (Cole & Maxwell, 2003; Ledgerwood & Shrout, 2011; Fritz et al., 2016). Since most measures in psychology are not perfectly reliable, and since latent variable approaches correct for unreliability, latent variable approaches to mediation are more powerful than approaches with only manifest variables such as simple path or regression analysis.

Latent variable approaches to mediation analysis are relatively straightforward extensions of manifest mediation analysis (MacKinnon, 2008), but rely on an underlying measurement structure for each of the latent variables. Latent variables are typically specified using multiple manifest indicators (Bollen, 1989). For example, a latent variable called *depression* might be specified with three indicators: self-reported depression, a clinician report of depression, and mother report of depression. Shared variability from the different indicators encompass the latent variable, and unshared variability is assumed to be measurement error. The latent variable depression can be related to other variables in a mediation framework in similar fashion as manifest variables. The advantage of using latent variables in mediation analysis is to correct for unreliability, which disattenuates estimates of the mediated effect (Fritz et al., 2016).

Latent variables are generally measured with multiple indicators, and sometimes indicators are different methods found in multimethod designs. In the example above, depression is measured by self- clinician- and mother-reports; a multimethod design. The most basic measurement structure of latent variables would assume that unshared variance among the three methods are measurement error, which may be incorrect in a multimethod framework (e.g., De Los Reyes, 2011; Eid, Geiser, & Koch, 2016). It is quite likely that a portion of unshared variability is due to systematic method effects (Fiske, 1982; Fiske & Campbell, 1992; Podsakoff, MacKenzie, & Podsakoff, 2012). Systematic method effects occur when correlations are stronger between the same method measuring different constructs than between constructs measured by different methods, in accordance with multitrait-multimethod (MTMM) designs (Campbell & Fiske, 1959; Fiske & Campbell, 1992). Method effects, if incorrectly managed, can lead to bias in relationships among variables across various fields of social science research (Doty & Glick, 1998).

To address method effects in mediation analysis, one more recent approach combined a latent variable path analysis mediation model with a multimethod measurement structure known as the correlated traits-correlated method–1 (CT-C[$M - 1$]) model (Papa et al., 2015). The so-called multimethod mediation model is a structural equation modeling approach that allows researchers to account for a multimethod measurement structure and random measurement error while examining structural relationships among variables. Such a model is a step in the right direction for evaluating data using multimethod designs and creating latent variable multimethod statistical tools. The proposed M4 model will, in part, build on the multimethod mediation modeling approach.

## Moderation Analysis

Conceptually, moderation is the effect of one variable influencing the relationship between two variables. Computationally, a moderated effect is equivalent to an interaction effect, where an outcome is regressed on the product term of two or more variables. Given one dependent variable *Y*, one independent variable *X*, and one moderating variable *W*, the equation for examining simple moderation is:

$$Y = i_Y + b_1X + b_2W + b_3XW + e_Y \tag{4}$$

where $b_1$, $b_2$, and $b_3$ are the regression paths between variables, $e$ indicates the residual error, $X$, $W$, and $Y$ indicate the manifest variables, and $XW$ indicates the interaction (or product) term. Both a conceptual model and path model are shown in Figure 1.2.

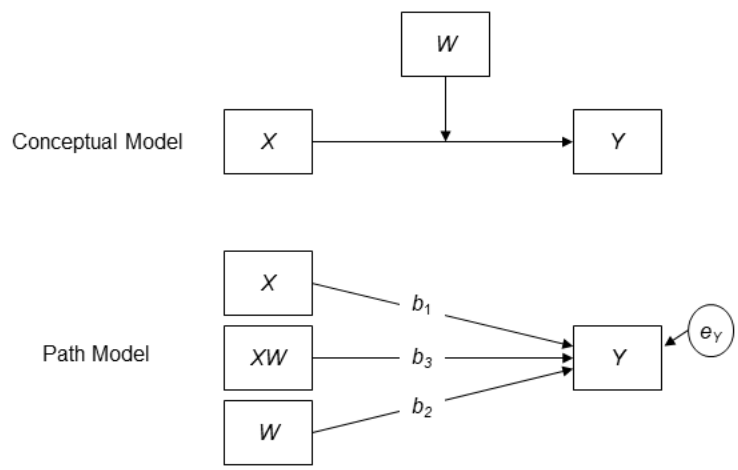


**Figure 1.2**: Simple moderation model

Examining moderating effects for manifest variables is theoretically simple. Every participant, $p$, in the dataset has value of $X_p$ and $W_p$. $X_p$ can be multiplied by the value of $W_p$ for each participant. The newly created product term, $XW$, is a manifest variable that indicates the interaction between $X$ and $W$ for each participant. The $XW$ product term can be included in regression models that include main effects of both the $X$ and $W$ terms. Moderating effects are examined under modeling approaches that assume low collinearity between the product term $XW$ and its first-order predictors, $X$ and $W$ (Aiken & West, 1991). To properly estimate interaction effects void of collinearity, mean centering is recommended (Aiken & West, 1991). Mean centering not only reduces collinearity, but also aides in interpreting the interaction effect.

Similar to mediation analysis, results from moderation analysis can be attenuated when measurement error is present in the manifest variables (Evans, 1985). It is thus suggested that moderated effects be examined using latent moderation analysis.

Unlike the relatively straightforward extension of mediation analysis to latent variable approaches, the extension of moderation analysis to latent variables approaches is not simple. The manifest approach to moderation analysis requires creating a product of the independent variable with the moderating variable *for each participant*. However, latent variable approaches, by definition, contain values that are not directly observed for each participant. Methods to examine latent interaction terms have been developed and researched since the mid-1980s, and are complex.

The earliest approaches to studying latent variable interactions used observed variables to create *product indicators* as the measurement model for the latent interaction term (Kenny & Judd, 1984). Two drawbacks in this approach are that 1) product indicators were created using unreliable manifest variables, which led to especially unreliable latent interaction terms (Moosbrugger, Schermelleh-Engel, & Klein, 1997), and 2) the method required imposing complex nonlinear constraints on the model to account for the inevitable non-normal distribution of the product indicators.

In response to the original approach for creating latent interaction effects using product indicators, different approaches for examining latent interaction terms emerged. Moosbrugger and colleagues (1997) conducted a review of approaches used to estimate latent variable interaction effects. They described ten approaches, grouping them into three categories: methods that (incorrectly) assumed normality of the indicator variables (three approaches), methods with distribution-free assumptions about the indicator variables (six approaches), and methods that (correctly) assumed indicator variables were non-normally distributed (one approach). Methods assuming normality of the indicator variables led to “underestimation of standard errors and biased chi-square values” (p. 103), likely because the distribution of an interaction term is not normally distributed (Moosbrugger et al., 1997). Four distribution-free methods resulted in asymptotically unbiased estimation but required large sample sizes in practical applications. One distribution-free method (two-stage least squares [2SLS]) resulted in unbiased estimation but had rather low power. The fifth distribution-free method was a Bayesian Analysis of Latent Variable Models, and a small simulation study resulted in biased parameter estimates and large standard errors. Of the distribution-free methods, the 2SLS method was the most promising as an avenue for evaluating latent interaction effects.

The only method for examining latent interaction effects that correctly assumed a non-normal distribution of the indicator variable was the latent moderated structural equations (LMS) method. The LMS method provided unbiased interaction terms and resulted in no standard error bias (Klein & Moosbrugger, 2000) when evaluated in a simulation study. Further, the LMS method outperformed other methods, and was more efficient than the 2SLS method, which was its closest competitor (Klein & Moosbrugger, 2000).

The LMS approach, unlike other approaches to latent variable interaction effects, does not directly estimate product values between indicators. Instead, the LMS approach uses an iterative expectation maximization (EM) algorithm to estimate the interaction effect. Klein and Moosbrugger (2000) recommend the LMS method for evaluating latent interaction terms. Currently, the LMS method is still used when evaluating latent interaction terms, and this method is the standard for evaluating latent interaction effects at this time. The LMS approach is readily available in the M*plus* software (Muthén & Muthén, 1998-2018), which was used throughout the course of this project. The M4 approach implemented the LMS technique to examine latent moderated effects.

**Moderated Mediation Analysis**

Combining moderation with mediation is a relatively simple process using manifest path analysis (Edwards & Lambert, 2007). In the most generalizable form of moderated mediation analysis using manifest path analysis, all pathways between $X$, $M$, and $Y$ may vary across levels of the moderating variable, $W$ (Edwards & Lambert, 2007; Hayes, 2013). The complexity of moderating effects in a mediation analysis is that the moderating variable can interact with any (or even multiple) predictor variables and influence any (or multiple) outcome variables (Edwards & Lambert, 2007; Hayes, 2013; Hayes, 2015). Further, any reasonable number of $M$ and $W$ variables can be specified, leading to structurally complex models. For the nature of this project, examining a simple moderated mediation model with one moderator and one mediator sufficed. Even so, with just one moderator and one mediator, seven distinct moderated mediation models could have been created (Edwards & Lambert, 2007), with each model referring to the moderating effect of all possible combinations of the $a$, $b$, and $c'$ pathways of the mediation model. For the present project, only first-stage moderation, where the moderating variable, *W*, interacts with the *X* variable and influences only the *M* variable and the *a* path, were examined (see Figure 1.3).

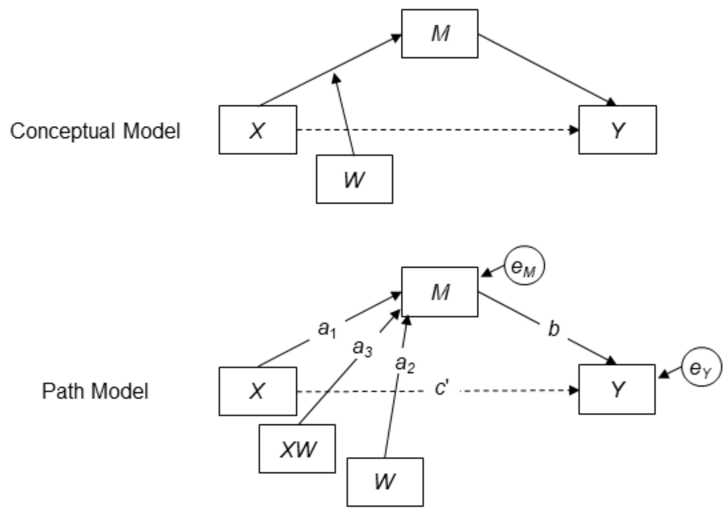


**Figure 1.3**: First-stage moderated mediation model

An equation for a path analysis moderated mediation model with first-stage moderation is given, first in two equations, one for each outcome variable:

$$M = i_M + a_1X + a_2W + a_3XW + e_M \tag{5}$$

$$Y = i_Y + c'X + bM + e_Y \tag{6}$$

where $i$ indicates the intercept, $a_1$, $a_2$, $a_3$, $b$, and $c'$ are the regression paths between variables, $e_M$ indicates the residual error of the mediator, $e_Y$ indicates the residual error of the final outcome variable, and $X$, $M$, $W$, and $Y$ indicate the variables. Combining Equations 5 and 6 allows restructuring the equations to formally denote the moderating effect, according to simple slopes (Aiken & West, 1991; Edwards & Lambert, 2007):

$$
\begin{aligned}
Y &= i_Y + c'X + b\left(i_M + a_1X + a_2W + a_3XW + e_M\right) + e_Y \\
&= i_Y + c'X + bi_M + ba_1X + ba_2W + ba_3XW + be_M + e_Y \\
&= i_Y + bi_M + (c' + a_1b)X + (a_2b)W + (a_3b)XW + be_M + e_Y \\
&= [i_Y + (i_M + a_2W)b] + [c' + (a_1 + a_3W)b]X + be_M + e_Y
\end{aligned}
\tag{7}
$$

The simple slopes restructure of simple first-stage moderated mediation analysis shows that the indirect effect, $a_1b$ in simple mediation, is influenced by the moderating variable so that now the indirect effect is $(a_1 + a_3W)b$. This equation was used to quantify the structural relationships in the proposed M4 model.

The model presented in Equation 7 and Figure 1.3 uses manifest variables. Because both mediated and moderated effects are attenuated by measurement error, it is important to create a moderated mediation model that models measurement error. Latent variable approaches are a solution to addressing measurement error.

In a recent advancement to moderated mediation analysis, Cheung and Lau (2017) developed a latent variable structural equation modeling approach to moderated mediation analysis and compared their approach to manifest regression moderated mediation analysis. Figure 1.4 depicts a moderated mediation model using latent factors each measured by three manifest variables. Cheung and Lau found that even with adequate reliability, estimates of the mediated pathways in the manifest regression moderated mediation model were attenuated by 5 to 20% without controlling for measurement error. Furthermore, estimates of the moderated pathway were attenuated by 30% without controlling for measurement error. Additionally, confidence intervals were biased in the regression approach when reliabilities were low. Thus, when variables were not perfectly reliable, or in other words when variables contained error, estimates from moderated mediation analysis were attenuated. These findings mimic results that measurement error attenuates both the mediated effect (Hoyle & Kenny, 1999) and the moderated effect (Evans, 1985).

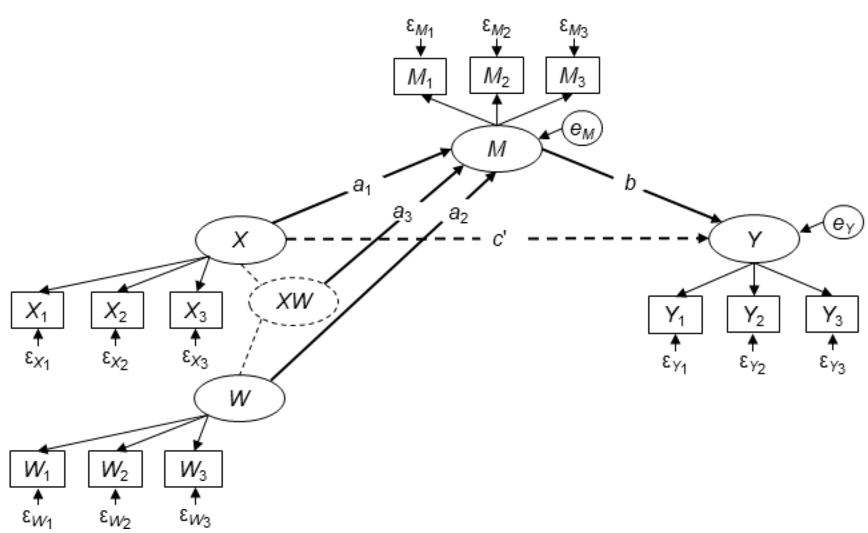


**Figure 1.4**: First-stage latent variable moderated mediation model. All factors are measured with three manifest indicators.

The proposed M4 model will use first-stage moderated mediation. Further, the M4 model will build on the latent variable structural equation modeling approach to moderated mediation analysis.

**Multimethod Designs**

It is widely recommended in psychology research to use multimethod designs (Achenbach, 2011; De Los Reyes & Kazdin, 2005; Eid & Diener, 2006). Multimethod designs assess constructs using multiple, independent methods of measurement, which can offer differing perspectives on the constructs of interest. To what extent do different methods agree or disagree on the measurement of a construct? Are method agreement and method discrepancies meaningful? These are questions that many multimethod researchers, especially researchers using informants as methods, are interested in investigating (e.g. Achenbach, 2011; De Los Reyes, 2011; Dirks, De Los Reyes, Briggs-Gowan, Cella, & Wakschlag, 2012). Multimethod designs allow researchers to examine the extent to which different methods show agreement versus discrepancy when measuring constructs.

One of the most common ways to evaluate multimethod data is to use multitrait-multimethod (MTMM) analysis. MTMM analyses allow social scientists to study multiple traits as measured by multiple methods, and are commonly used to evaluate the convergent and discriminant validity of many psychological measures (Campbell &

Fiske, 1959; Eid, 2000; Eid, Nussbeck, Geiser, Cole, Gollwitzer, & Lischetzke, 2008; Jöreskog, 1971; Marsh, 1989; Widaman, 1985). Per the original MTMM approach (Campbell & Fiske, 1959), every measured construct contains at least two sources of influence: the underlying construct of interest (i.e., trait), and the method by which the construct is measured (i.e., method). In this original approach, each measurement of a construct is conceptualized as a trait-method unit (TMU). For example, when measuring anxiety, a clinician might ask an individual to self-report the occurrence of feeling nervous or not being able to sleep. The trait, anxiety, is thus measured using the method, self-report. Consequently, the TMU is self-reported anxiety.

Early approaches to MTMM analysis commonly focused on examining the correlations among TMUs using a single observed variable per TMU (Campbell & Fiske, 1959). For example, if a researcher was interested in examining anxiety and depression as reported by mothers and fathers, they would have one observed variable representing each: mothers' reports of anxiety, fathers' reports of anxiety, mothers' reports of depression, and fathers' reports of depression. Researchers could then examine the correlations among variables to determine the amount of variance shared across different methods measuring the same trait (convergent validity), and the amount of variance shared across the same method measuring different traits or different methods measuring different traits (discriminant validity). Comparisons of these correlations were thought to indicate levels of convergent and discriminant validity, with the ideal being that different methods would equally measure the same trait, and different traits would not be too highly correlated. Unfortunately, methods have been shown to differ in their measurement of traits (Bagozzi, Yi, & Phillips, 1991; Podsakoff, MacKenzie, Lee, &

Podsakoff, 2003; Podsakoff, MacKenzie, & Podsakoff, 2012; Schmitt & Stults, 1986). Many refer to the impact of methods on the measurement of traits as *method effects*.

To account for method effects, researchers use a combination of MTMM designs and sophisticated statistical methods. Presently, one of the most common ways to evaluate MTMM data is by using confirmatory factor analysis (CFA; Kenny & Kashy, 1992; Eid, Lischetzke, & Nussbeck, 2006; Jöreskog, 1971; Widaman, 1985). Although other methods, such as multilevel models can be used to examine method effects, their utility is limited when the classical MTMM design is employed. Maas, Lensvelt-Mulders, and Hox (2009) describe how the multilevel MTMM model is a more restrictive form of the CFA-MTMM model. Specifically, the multilevel MTMM models imposes factor loadings constraints on all trait and method factors, thus the multilevel MTMM approach is less flexible than a CFA-MTMM approach. When data structures are complex, a larger number of methods were used to gather data, or the methods cannot be clearly distinguished, a multilevel framework may be more ideal. However, the CFA-MTMM approach is more useful because of its flexibility. CFA-MTMM (as well as multilevel MTMM) models also allow researchers to examine relationships among latent variables rather than observed variables, thus controlling for random measurement error.

**Correlated traits-correlated methods model.** One of the earliest CFA-MTMM models created was the correlated traits-correlated methods (CT-CM) model (Jöreskog, 1971; Widaman, 1985). The CT-CM model intuitively viewed TMUs as containing three distinct sources of influence: trait, method, and random measurement error.

Mathematically, every observed TMU $Y_{mt}$ is comprised of a $T_t$ trait factor, an $M_m$ method factor, and random measurement error $\varepsilon_{mt}$:

$$Y_{mt} = \lambda_{mt}T_t + \gamma_{mt}M_m + \varepsilon_{mt} \tag{8}$$

where *m* indicates the method, *t* indicates the trait, $\lambda_{mt}$ indicates the trait factor loading, and $\gamma_{mt}$ indicates the method factor loading. Trait factors correlate with one another and method factors correlate with one another, but trait factors are not allowed to correlate with method factors. Error terms, likewise, are not allowed to correlate with trait nor method factors. Error terms are also not allowed to correlate with one another. Figure 1.5 depicts an example CT-CM model with four observed TMUs, two trait factors $T_t$, two method factors $M_m$, and four error variables $\varepsilon_{mt}$.

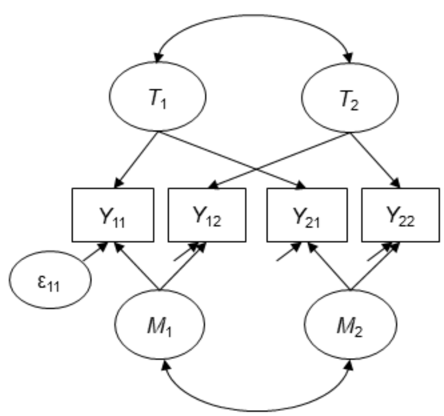


**Figure 1.5**: Correlated traits-correlated method (CT-CM) measurement model

Although intuitively appealing, simulation designs have shown that the CT-CM model is not globally identified, often fails to converge, and estimates improper solutions (Castro-Schilo, Widaman, & Grimm, 2013; Marsh, 1989). Further, estimates from the CT-CM model can be difficult to interpret because the model does not define what the different factors truly measure. For example, it is unclear what the method factors measure compared to trait factors since there is no point of reference for comparison.

**Correlated traits-correlated uniqueness model.** To address the estimation problems with the CT-CM model, Marsh (1989) recommended using the correlated traits-correlated uniqueness (CT-CU) model, which does not have the same convergence problems. Originally proposed by Kenny (1976), the CT-CU model consists of $T_t$ trait factors and $\varepsilon_{mt}$ error terms but does not include method factors. Instead, all error terms measured by the same method, *m*, are allowed to correlate. Unfortunately, this model lacks parsimony because many error covariances must be estimated for models that include many methods per trait. Further, the CT-CU model confounds method effects with random measurement error. Method effects are not necessarily measurement error (De Los Reyes, 2011; Eid, Geiser, & Koch, 2016), but rather are consistent and reliable variance pertaining to the method of measurement. Defining method effects as measurement error leads to underestimation of the reliability of TMUs. An example CT-CU model depicting four observed TMUs, two trait factors $T_t$, and correlated errors $\varepsilon_{mt}$ for TMUs measured with the same method *m* is shown in Figure 1.6.

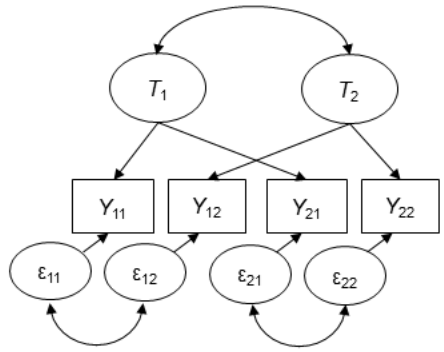


**Figure 1.6**: Correlated traits-correlated uniqueness (CT-CU) measurement model

**Correlated traits-correlated (methods – 1) model.** Eid (2000) proposed an MTMM model to address the limitations found in the CT-CM and CT-CU model. Known as the correlated traits-correlated (methods – 1) (CT-C[$M$ – 1]) model, this model calls on classical test theory (Lord & Novick, 1968; Novick, 1966) to define latent trait and method variables. In Eid's framework, TMUs are not inherently separable into trait influences and method influences, but rather are defined depending on whether they are measured with the reference method or a non-reference method. The trait factors are contingent upon the so-called reference method, which is the gold-standard to which all convergent validity and method-specificity conclusions are interpreted. The TMUs specific to the reference method do not have a method factor. As such, $T$ trait factors and $M$ – 1 method factors are defined in this approach. The trait factors ( $T_{1t}$ ) are defined as the trait measured by the reference method while method factors ( $M_m$ ) are defined as the residual influence of the non-reference methods that is not shared with the reference method. A CT-C[$M$ –1]) measurement model with four observed TMUs, two trait factors pertaining to the reference method $T_{1t}$, one non-reference method factor $M_m$, and four error variables $\varepsilon_{mt}$ is shown in Figure 1.7.

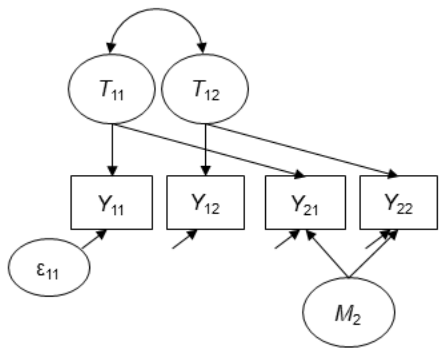


**Figure 1.7**: Correlated traits-correlated (method – 1) (CT-C[$M$ –1]) measurement model

Mathematically, TMUs not pertaining to the reference factor ($m \neq 1$) are comprised of a trait factor specific to the reference method ($T_{1t}$), a method residual factor ($M_m$), and random measurement error ($\varepsilon_{mt}$). TMUs pertaining to the reference factor ($m$ = 1) are comprised of a trait factor specific to the reference method ($T_{1t}$), and random measurement error ($\varepsilon_{mt}$), but no method residual factor. An equation for this model is given as:

$$Y_{mt} = \lambda_{mt} T_{1t} + \gamma_{mt} M_m + \varepsilon_{mt}\text{, for } m \neq 1 \tag{9}$$

$$Y_{1t} = \lambda_{1t} T_{1t} + \varepsilon_{1t}\text{, for } m = 1 \tag{10}$$

where $m$ indicates the method, $t$ indicates the trait, $\lambda_{mt}$ indicates the trait factor loading, and $\gamma_{mt}$ indicates the method factor loading.

The advantages of the CT-C($M$ – 1) model are that it is globally identified, it does not have the same convergence problems as the CT-CM model, and it does not define method effects as measurement error as in the CT-CU model. However, the original version of the CT-C($M$ – 1) model assumes only one indicator per TMU, which imposes the strict assumption that method effects equally influence all traits being measured, an unrealistic assumption (Eid et al., 2003).

**Multiple indicator CT-C($M$ – 1) model.** A multiple indicator CT-C($M$ – 1) model addresses the limitation that traits are equally influenced by method effects (Eid et al., 2003). Unlike the single indicator approach, each TMU is measured using multiple indicators $i$. Mathematically, the multiple-indicator CT-C($M$ – 1) model is similar to the single-indicator model, but includes indicator-specific factor loadings ($\lambda_{imt}$ and $\gamma_{imt}$), and trait specific methods ($M_{mt}$). The measurement equations for this model are:

$$Y_{imt} = \lambda_{imt}T_{1t} + \gamma_{imt}M_{mt} + \varepsilon_{imt}\text{, for } m \neq 1 \tag{11}$$

$$Y_{i1t} = \lambda_{i1t}T_{1t} + \varepsilon_{i1t}\text{, for } m = 1 \tag{12}$$

where *i* indicates the indicator, *m* indicates the method, *t* indicates the trait, $\lambda_{imt}$ indicates the trait factor loading, and $\gamma_{imt}$ indicates the method factor loading. Because multiple indicators are used, the method factor, *M*, is not only specific to the method (subscript *m*), but also to the trait (subscript *t*). The multiple indicator CT-C(*M* – 1) model with eight observed TMUs, two trait factors $T_{1t}$, one non-reference method factor per trait $M_{mt}$, and eight error variables $\varepsilon_{imt}$.

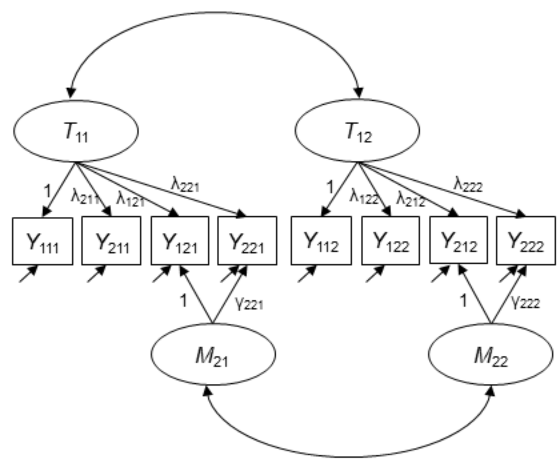


**Figure 1.8**: Multiple indicator CT-C(*M* –1) measurement model

**Multiple indicator CT-C(*M* – 1) model with indicator-specific trait factors.** One complication that can arise in the multiple indicator model is when multiple indicators of the same trait do not perfectly measure the same trait factor, resulting in poor model fit. Indicators of a single trait may measure slightly different facets of a trait due to differences in item wording or response anchors. Indicator heterogeneity can be modeled in the CT-C(*M* – 1) framework by introducing indicator-specific trait factors. The multiple-indicator CT-C(*M* – 1) model with indicator-specific trait factors is nearly identical to the multiple-indicator CT-C($M - 1$) model without indicator-specific trait factors, but includes indicator specific traits ($T_{i1t}$). The measurement equations for this model are:

$$Y_{imt} = \lambda_{imt} T_{i1t} + \gamma_{imt} M_{mt} + \varepsilon_{imt}\text{, for } m \neq 1 \tag{13}$$

$$Y_{i1t} = \lambda_{i1t} T_{i1t} + \varepsilon_{i1t}\text{, for } m = 1 \tag{14}$$

where *i* indicates the indicator, *m* indicates the method, *t* indicates the trait, $\lambda_{imt}$ indicates the trait factor loading, and $\gamma_{imt}$ indicates the method factor loading. Because multiple indicators are used, the trait factor, *T*, is not only specific to the trait (subscript *t*), but also the indicator (subscript *i*). Figure 1.9 depicts this multiple indicator CT-C(M – 1) model with indicator-specific traits. Similar to Figure 1.8, the model depicts eight observed TMUs, one non-reference method factor per trait, and eight error variables $\varepsilon_{imt}$. However, the model now depicts four indicator-specific trait factors, $T_{i1t}$, instead of general trait factors.

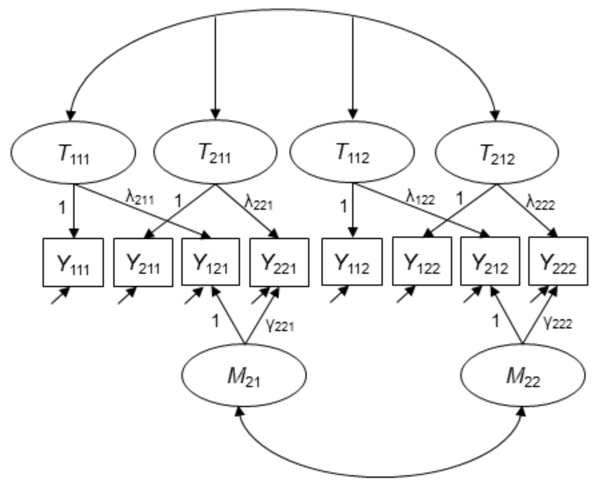


**Figure 1.9**: Indicator-specific CT-C($M$ –1) measurement model

The multiple indicator CT-C($M$ – 1) model both with and without indicator-specific trait factors addresses limitations in prior MTMM models, particularly 1) the convergence and interpretability problems in the CT-CM model, 2) the confound between method effects and error in the CT-CU model, and 3) the inherent assumption in the CT-CM and single indicator CT-C($M$ – 1) models that method effects are consistent across traits (i.e., method effects are not trait-specific).

The M4 model was created for the multiple indicator CT-C($M$ – 1) model both with and without indicator-specific trait factors.

**Design oriented approaches.** Other MTMM models have been created to address specific measurement issues and to examine new questions using MTMM analysis. Particularly, researchers have noted that different types of methods require different measurement models to properly evaluate method effects (Eid et al., 2008; Eid et al., 2016; Nussbeck, Eid, Geiser, Courvoisier, & Lischetzke, 2009) and that choosing the incorrect multimethod model can result in non-converged and improper solutions (Geiser, Bishop, & Lockhart, 2015). Two different types of methods have been identified: interchangeable methods and structurally different methods. Interchangeable methods are methods which can be randomly chosen from a set of theoretically equivalent methods (e.g., students evaluating their professor). When researchers gather data using interchangeable methods, an appropriate CFA-MTMM model is one with an "average" trait factor and uncorrelated residual method factors (Nussbeck et al., 2009). Structurally different methods are methods that cannot be chosen at random, and each method is theoretically distinct from other methods (e.g., mother compared to teacher reports of a child's behavior). When researchers use structurally different methods, an appropriate CFA-MTMM model is the CT-C($M - 1$) model (Eid et al., 2008; Eid et al., 2016). In psychology, it is much more common to find structurally different methods than interchangeable methods. The current M4 model was created for structurally different methods. Therefore, the multiple indicator CT-C($M - 1$) model served as the underlying measurement structure of the M4 model.

# CHAPTER III

# CREATING THE M4 MODEL AND DEFINING EFFECTS

The M4 model combined a CT-C($M$ – 1) measurement structure with first-stage moderated mediation analysis using a latent variable framework. Any number of indicators, methods, and traits could be implemented into the model, and any stage of moderated mediation could potentially be utilized. For the current project, the M4 model included two methods and three indicators per $X$, $M$, $W$, and $Y$ trait factors to match the dataset example presented in Chapter IV. Additional indicators and additional methods may be implemented into the approach, but using only two methods and three indicators simplified the presentation and discussion of the model. The multiple indicator CT-C($M$ – 1) models both with and without indicator-specific trait factors were selected as the measurement portion for the new M4 model, while the first-stage moderated mediation path model was selected as the structural portion of the new M4 model.

The first step in creating the M4 model was to create a CT-C($M$ – 1) model with four traits, three indicators per trait, and two methods per indicator without and with indicator-specific trait factors as shown in Figures 2.1 and 2.2, respectively.

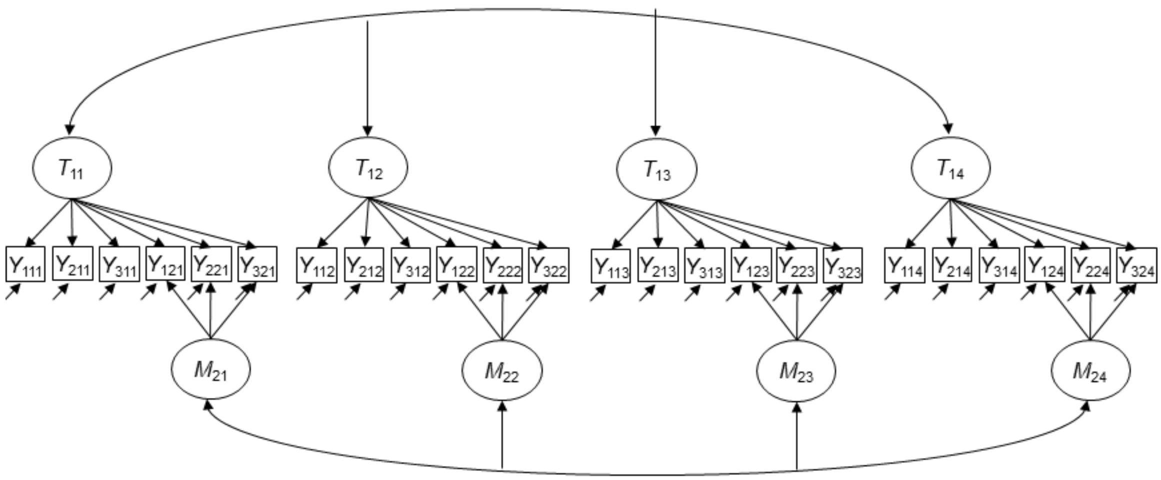


**Figure 2.1**: Multiple indicator CT-C($M$ –1) model

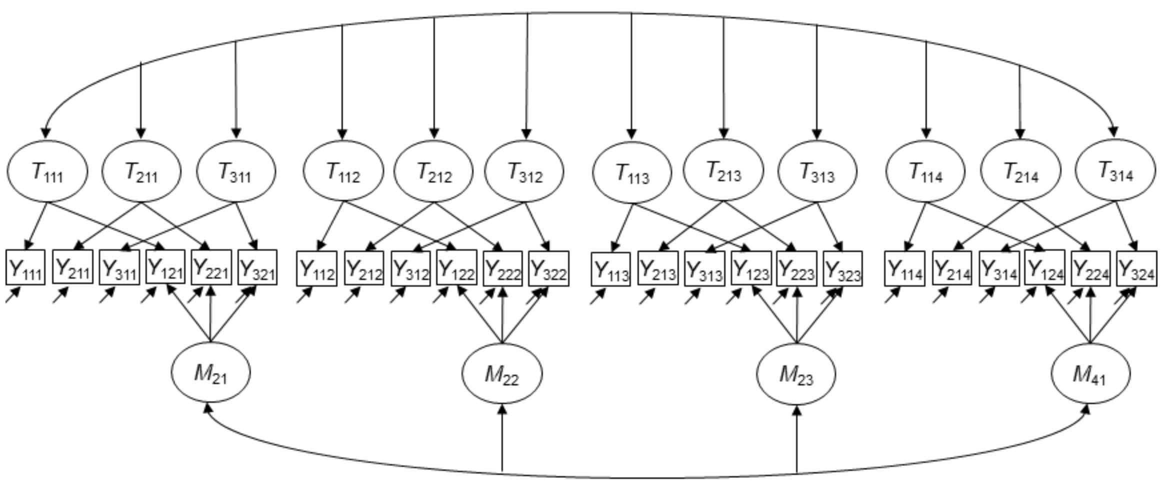


**Figure 2.2**: Multiple indicator CT-C($M$ –1) model with indicator-specific trait factors

Equations to identify the multiple indicator CT-C($M$ – 1) model with and without indicator-specific trait factors were presented in Chapter II. To fully define models within the context of the M4 approach, an intercept, $\alpha_{imt}$, was added to the original measurement equations since latent trait means of the M4 model must be constrained to 0 (or centered) in order to later estimate and interpret the latent interaction term. The measurement equations for observed indicators of the CT-C($M$ – 1) model *without* indicator-specific trait factors (Figure 2.1) are shown below.

$$Y_{imt} = \alpha_{imt} + \lambda_{imt} T_{1t} + \gamma_{imt} M_{mt} + \varepsilon_{imt}\text{, for } m \neq 1 \tag{15}$$

$$Y_{imt} = \alpha_{imt} + \lambda_{imt} T_{1t} + \varepsilon_{imt}\text{, for } m = 1 \tag{16}$$

Equations 15 and 16 show that each observed non-reference method indicator ($m \neq 1$) is regressed on the intercept parameter, a trait factor, a trait-specific method factor, and an error variable while each observed reference method indicator ($m = 1$) is regressed on the intercept parameter, a trait factor and an error variable. For the CT-C($M$ – 1) model *with* indicator-specific trait factors, each observed non-reference method indicator ($m \neq 1$) is regressed on an indicator-specific trait factor, a trait-specific method factor, and an error variable while each observed reference method indicator ($m = 1$) is regressed on an indicator-specific trait factor and an error variable, as shown in Equations 17 and 18.

$$Y_{imt} = \alpha_{imt} + \lambda_{imt} T_{i1t} + \gamma_{imt} M_{mt} + \varepsilon_{imt}\text{, for } m \neq 1 \tag{17}$$

$$Y_{i1t} = \alpha_{imt} + \lambda_{imt} T_{i1t} + \varepsilon_{imt}\text{, for } m = 1 \tag{18}$$

The CT-C($M$ – 1) models serve as the measurement portion of the M4 models. There are important outcomes relevant to the M4 approach that can be assessed using these measurement models.

**Using the CT-C($M$ – 1) Models to Examine Consistency, Method-Specificity, and Reliability in the M4 Approach**

The extent to which the measurement of variables is influenced by trait effects, method effects, and random measurement error can be empirically studied using the M4 approach. In the CT-C($M$ – 1) measurement model, manifest variables are decomposed into three possible sources of variance: 1) variance due to the trait factor, 2) variance due to the method residual factor, and 3) variance due to neither the trait nor method residual factor, but due instead to random measurement error. These various sources of variance can be used to compute consistency, method-specificity, and reliability. Equations for consistency, method-specificity, and reliability are given for the CT-C($M$ – 1) model with indicator-specific factors and can be generalized to the CT-C($M$ – 1) model without indicator-specific factors.

Consistency is defined as the proportion of observed variance in a manifest variable that is due to the trait factor. Here, it is important to recall that the trait factor is specific to the reference method. It is thus appropriate to state that consistency is the proportion of observed variance in each manifest variable that is shared with the reference method. Consistency can be calculated for all manifest variables.

$$Con(Y_{imt}) = \frac{\lambda_{imt}^2 Var(T_{i1t})}{\lambda_{imt}^2 Var(T_{i1t}) + \gamma_{imt}^2 Var(M_{mt}) + Var(\varepsilon_{imt})} \tag{19}$$

Method-specificity is defined as the proportion of observed variance that is due to method residual effects. Method residual effects contain variance specific to a given method (e.g., father report) that is not shared with the reference method. Method-specificity is calculated for all non-reference method manifest variables.

$$Mspe(Y_{imt}) = \frac{\gamma_{imt}^2 Var(M_{mt})}{\lambda_{imt}^2 Var(T_{i1t}) + \gamma_{imt}^2 Var(M_{mt}) + Var(\varepsilon_{imt})}, \text{ for } m \neq 1 \tag{20}$$

Reliability is the proportion of observed variance that is due to the sum of trait and method residual effects, and not random measurement error. For each trait-method unit, consistency plus method-specificity equals reliability. Reliability can be calculated for all manifest variables.

$$Rel(Y_{imt}) = \frac{\lambda_{imt}^2 Var(T_{i1t}) + \gamma_{imt}^2 Var(M_{mt})}{\lambda_{imt}^2 Var(T_{i1t}) + \gamma_{imt}^2 Var(M_{mt}) + Var(\varepsilon_{imt})} \tag{21}$$

Consistency and method-specificity are used to determine the extent to which measurements share variability with the reference method (i.e., convergent validity), and the extent to which measurements contain variability that is not shared with the reference method. Reliability can be used to determine the extent to which measurements are void of random measurement error. These outcomes can be used in the M4 approach to determine the impact of method effects and measurement error on manifest variables.

**Combining the CT-C($M$ – 1) Models with Moderated Mediation Analysis**

The creation of the M4 model without indicator-specific trait factors was simple and straightforward. Each trait factor was conceptualized as $X$, $M$, $W$, or $Y$, and correlations among trait factors are appropriately changed regression paths among trait factors. The M4 model without indicator-specific trait factors is shown in Figure 2.3.

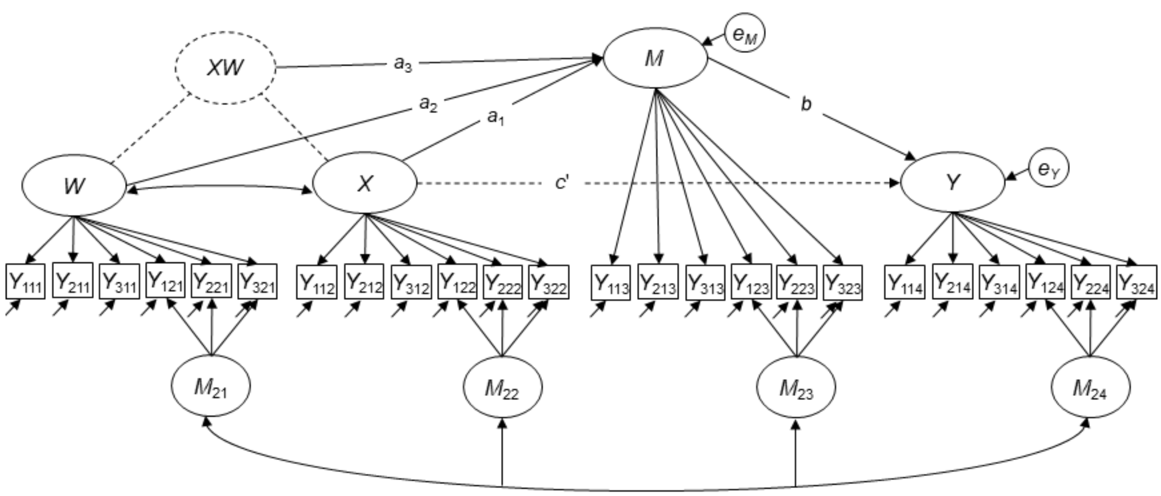


**Figure 2.3**: M4 model with non-indicator-specific general trait factors

Creating the M4 model with indicator-specific trait factors was a more complex process. Equations 16 and 17 as well as Figure 2.2 suggest the presence of as many indicator-specific trait factors as there are indicators, raising the question of how best to address all potential moderated mediation effects. Theoretically, it was possible to estimate any or all indicator-specific moderated and mediated effects, but doing so would result in a highly complex model that may not be identified.

Indicator-specific factors, theoretically, measure slightly different facets of a single construct due to minor measurement differences, item wording, or otherwise. From a pragmatic perspective, trying to evaluate relationships among facets of constructs can be cumbersome and difficult; it was not only possible but also practical to combine indicator-specific factors into a single, homogeneous factor. Fortunately, there was a relatively straightforward way to mathematically reconfigure indicator-specific trait factors to create a common trait factor using what is called the latent means approach (Geiser, Koch, & Eid, 2014). Such an approach did not change the indicator-specific nature of the variables, but rather modeled the indicator-specific nature of variables in a manner more appropriate for examining relationships among constructs.

### Latent Means Approach to Create Common *X*, *M*, *W*, and *Y* Trait Factors

A simple way to reconfigure indicator-specific traits into a common trait with indicator-specific "residual" terms was by using the latent means approach (see Geiser, Koch, & Eid, 2014; Papa et al., 2015). In the latent means approach, a common trait factor and $I - 1$ indicator-specific factors are computed for each construct, where $I$ indicates the total number of indicators for the given trait. The M4 model contains, at minimum, four common trait factors, one each for the *X*, *W*, *M*, and *Y* constructs. Common trait factors $CT_{1t}$ are defined as the average of the indicator-specific trait factors.

$$CT_{1t} = \frac{\sum_{i=1}^{I} T_{i1t}}{I} \tag{22}$$

Simply computing the common trait factor results in a higher order factor that does not appropriately capture all indicator-specific trait variance in the model. The "extra" trait variance not captured by the common trait is captured by the indicator-specific factor $IS_{i1t}$. The $IS_{i1t}$ factor is defined as the deviation of the trait factor from the common trait.

$$IS_{i1t} = T_{i1t} - CT_{1t} \tag{23}$$

Because all indicator-specific factors are deviations from a common trait, the sum of all $IS_{i1t}$ values equals zero.

$$0 = \sum_{i=1}^{I} IS_{i1t} \tag{24}$$

This property indicates that each $IS_{i1t}$ factor is a function of all other $IS_{i1t}$ factors. If, for instance, the first $IS_{i1t}$ factor is subtracted from each side of the equation, then this factor can be defined as a function of all other indicators.

$$IS_{11t} = -\sum_{i=2}^{I} IS_{i1t} \tag{25}$$

Only $I - 1$ $IS_{i1t}$ factors are necessary to properly compute the latent means approach because the first indicator is mathematically defined as a function of all other indicators. The indicator-specific trait factors are thus a function of a common trait factor and $I - 1$ $IS_{i1t}$ factors.

$$T_{i1t} = CT_{1t} + \sum_{i=2}^{I} IS_{i1t} \tag{26}$$

$$T_{11t} = CT_{1t} - \sum_{i=2}^{I} IS_{i1t} \tag{27}$$

The latent means approach was combined with the indicator specific CT-C($M - 1$) measurement structure. Equations 26 and 27 can be substituted into the Equations 17 and 18, resulting in the following full measurement model using four equations:

$$Y_{imt} = \alpha_{imt} + \lambda_{imt}\left[CT_{1t} + \sum_{i=2}^{I} IS_{i1t}\right] + \gamma_{imt} M_{mt} + \varepsilon_{imt}\text{, for } i \neq 1 \text{ and } m \neq 1 \tag{28}$$

$$Y_{1mt} = \alpha_{1mt} + \lambda_{1mt}\left[CT_{1t} - \sum\nolimits_{i=2}^{I} IS_{i1t}\right] + \gamma_{1mt}M_{mt} + \varepsilon_{1mt}\text{, for } i = 1 \text{ and } m \neq 1 \quad (29)$$

$$Y_{i1t} = \alpha_{i1t} + \lambda_{i1t}\left[CT_{1t} + \sum\nolimits_{i=2}^{I} IS_{i1t}\right] + \varepsilon_{i1t}\text{, for } i \neq 1 \text{ and } m = 1 \quad (30)$$

$$Y_{11t} = \alpha_{11t} + \lambda_{11t}\left[CT_{1t} - \sum\nolimits_{i=2}^{I} IS_{i1t}\right] + \varepsilon_{11t}\text{, } i = 1 \text{ and for } m = 1 \quad (31)$$

The measurement model defined in Equations 28 through 31 for the CT-C($M$ – 1) model with indicator specific trait factors and higher order common trait factors is shown in Figure 2.4. The common trait factors were conceptualized as the $X$, $M$, $W$, and $Y$ latent factors necessary for implementing the M4 model.

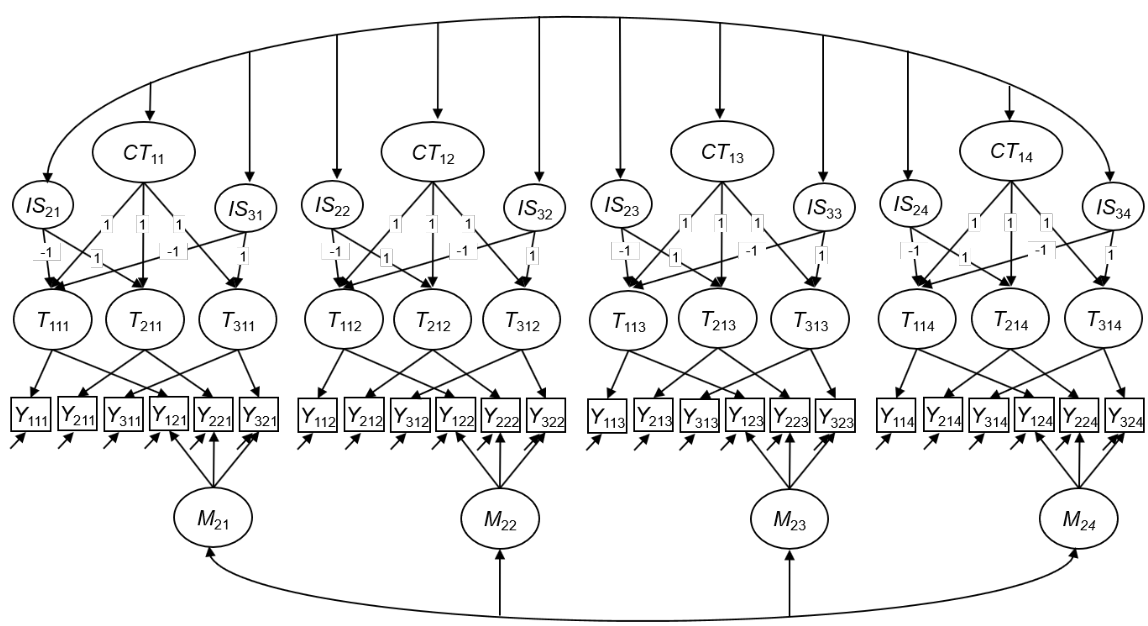


**Figure 2.4**: Latent means approach to create common trait factors

**Using the Common Trait Factors in First-Stage Moderated Mediation Models**

The common traits defined above served to create the latent *X*, *M*, *W*, and *Y* variables in the M4 model with indicator-specific trait factors. Replacing $CT_{1t}$ with *X*, *M*, *W*, or *Y* was how each latent factor in the M4 model was defined. For the M4 model without indicator-specific trait factors, replacing $T_{1t}$ with *X*, *M*, *W*, or *Y* was how each latent factor in the M4 model was defined. As a reminder, the following equation set was used to evaluate moderated mediation:

$$M = i_M + a_1 X + a_2 W + a_3 XW + e_M \quad (32)$$

$$Y = i_Y + c'X + bM + e_Y \quad (33)$$

$$Y = [i_Y + (i_M + a_2 W)b] + [c' + (a_1 + a_3 W)b]X + be_M + e_Y \quad (34)$$

where *X* indicates the latent independent factor, *M* indicates the latent mediating factor, *W* indicates the latent moderating factor, *XW* indicates latent interaction between the *X* and *W* factors, and *Y* indicates the latent dependent outcome. All $a$, $b$, and $c'$ coefficients indicate the paths between the latent factors, *i* represents the intercept, and $e$ represents the residual error terms of the endogenous *M* and *Y* latent factors. Figure 2.5 shows the M4 with common trait factors.

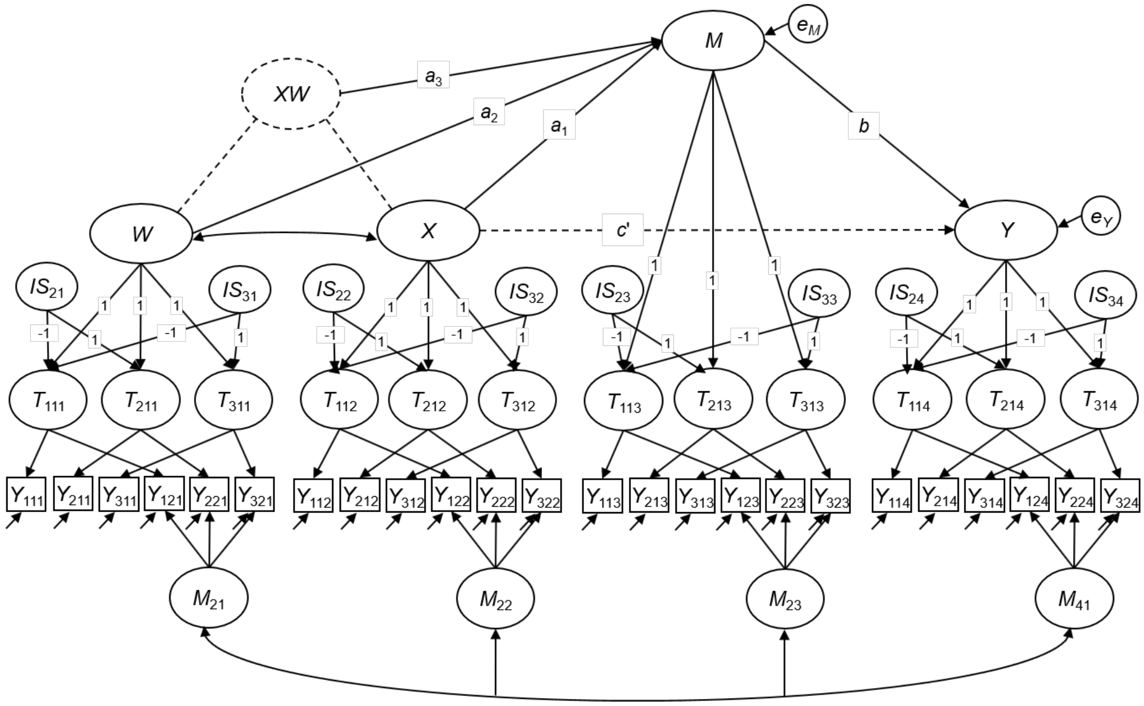


**Figure 2.5**: M4 model with indicator-specific common trait factors

The last parameter to identify in the M4 approach was the *XW* interaction term. This term is an interaction between two unmeasured constructs. By definition, latent variables are not directly observed for each individual, requiring the latent interaction term to be identified differently than in manifest moderation analysis. Namely, the latent interaction term is unmeasured. Modern approaches recommend using the latent moderated structural equations (LMS) approach (Klein & Moosbrugger, 2000) to estimate the latent interaction term, resulting in a variable that has no mean nor variance and only adds one parameter, the $a_3$ path, to the model (Muthén & Asparouhov, 2012). This approach is readily implemented in M*plus* 8.1 (Muthén & Muthén, 1998-2018), the software that was used to estimate the M4 models. Following guidelines from the first application of latent variable moderated mediation using continuous moderating variables (Cheung & Lau, 2017), the M4 approach used LMS to examine latent interaction effects.

### The Latent Interaction Term, *XW*

Klein and Moosbrugger (2000) developed an approach to empirically examine the latent interaction term. In their approach, a generalized latent interaction term can be created using a finite mixture approach applied to an elementary latent interaction effect. An elementary interaction term (Kenny & Judd, 1984) model containing a single interaction is mathematically defined as:

$$\eta = \alpha + \gamma_1 \xi_1 + \gamma_2 \xi_2 + \gamma_3 \xi_1 \xi_2 + \zeta \tag{35}$$

This elementary interaction model can be generalized to a model containing multiple interaction terms (Klein & Moosbrugger, 2000) by extending the model from scalar form to matrix form:

$$\eta = \alpha + \mathbf{\Gamma}\xi + \xi'\mathbf{\Omega}\xi + \zeta \tag{36}$$

"where $\eta$ is a $(1 \times 1)$ latent endogenous variable, $\alpha$ is an $(1 \times 1)$ intercept term, $\xi$ is a $(n \times 1)$ vector of latent exogenous variables, $\mathbf{\Gamma}$ is the $(1 \times n)$ coefficient matrix giving $\xi$'s effect on $\eta$, $\mathbf{\Omega}$ is the $(n \times n)$ coefficient matrix giving the impact of the product terms

$\xi_i\xi_j$ ($i < j$) on $\eta$, and $\zeta$ is the $(1 \times 1)$ disturbance variable with $E(\zeta) = 0$ and $\text{Cov}(\zeta, \xi') = 0$." (Klein & Moosbrugger, 2000, p. 460).

Compared to the elementary interaction model, the LMS approach evaluates multiple estimates of the latent interaction effect (thus the need for the generalized model presented in Equation 36), combining estimates using a joint distribution of the indicator variables. Specifically, "the distribution of the joint indicator vector $(\mathbf{x}, \mathbf{y})$ [where **x** is a vector of observed indicators for the exogenous variable(s) and **y** is a vector of observed indicators for the endogenous variable(s)] can be represented as a finite mixture of multivariate normal distributions" (Klein & Moosbrugger, 2000, p. 461). The LMS approach accounts for the nonnormal distribution of the latent interaction terms using this approach. Throughout the estimation of the interaction term, product values between indicators are not estimated; rather, the LMS approach requires using an iterative expectation maximization (EM) algorithm. The approach stops when the loglikelihood value is maximized. Results from the LMS approach can be interpreted in the same manner as other latent variable analyses.

**Using the M4 Model to Examine Moderated Mediation**

Moderation, mediation, and moderated mediation (i.e., whether the mediated effect varies across levels of the moderator) can be examined by evaluating the statistical and practical significance of the appropriate pathway (Hayes, 2015). In this section, it is discussed how to statistically evaluate mediation, moderation, and moderated mediation in the M4 model.

**Evaluating mediation.** The mediated effect is the process from *X* to *Y* through *M* and is mathematically reflected in the product $a_1 \times b$ in the M4 model. Although mediated effects may be examined using traditional hypothesis testing approaches (e.g., Sobel, 1982; Baron & Kenny, 1986), such approaches are prone to bias. Traditional hypothesis testing approaches require underlying assumptions of a normal sampling distribution, which is not reflected in the mediated effect. The mediated effect is a product term which results in an asymmetric sampling distribution (Bollen & Stine, 1990), and traditional hypothesis testing approaches are therefore not typically accurate for testing the significance of the mediated effect.

Presently, the best-practice approach for testing the mediated effect is the bias-corrected bootstrap (MacKinnon, 2008; Williams & MacKinnon, 2008). Bias-corrected bootstrap is a resampling technique in mediation analysis that draws *k* samples of size *n* with replacement to construct a sampling distribution with *k* estimates of the indirect effect. Endpoints are adjusted to correct for bias from outlying cases. From the *k* estimates, a confidence interval is calculated. Bias-corrected bootstrap is one of the most powerful methods for testing mediating effects (Williams & MacKinnon, 2008), and is recommended by leading researchers in mediation analysis (MacKinnon, 2008) and moderated mediation analysis (Hayes, 2013).

**Evaluating moderation.** The implemented method for examining latent interaction effects in M*plus* (Muthén & Muthén, 1998-2018) is the LMS approach (Klein & Moosbrugger, 2000). Creating a latent interaction using the LMS approach requires an iterative expectation maximization (EM) algorithm. Following guidelines by the first application of latent variable moderated mediation (Cheung & Lau, 2017) and guidelines suggested for latent moderation (Klein & Moosbrugger, 2000; Moosbrugger et al., 1997), the M4 model was estimated using LMS approach to examine interaction effects. The moderating effect was examined in relation to its influence on the mediation pathways.

**Evaluating moderated mediation.** To determine the extent to which moderators influence mediated pathways, Hayes (2015) developed the index of moderated mediation (Index MM). In first-stage moderated mediation, the moderating factor, *XW*, influences the *a*-pathway, resulting in a new path, $a_3$ (refer to Figure 2.3). Since the *a*-path is moderated, the overall moderated mediation effect ($\omega$, as denoted in Hayes, 2015) is a product of the conditional effect of *X* on *M*, $a_1 + a_3W$, and the effect of *M* on *Y*, *b*:

$$\omega = (a_1 + a_3W) \times b \tag{37}$$

Overall, moderated mediation is a way of representing that the indirect effect (i.e., the effect of *X* to *M* to *Y*) is a function of *W*. The equation above has an equivalent simple slopes form:

$$\omega = a_1 b + a_3 bW \tag{38}$$

where $a_1 b$ represents the intercept, and $a_3 b$ represents the slope. The $a_3 b$ estimate is what Hayes (2015) calls the index of moderated mediation (Index MM) in first-stage moderated mediation models. Should the indirect effect be unrelated $W$, then the resulting $a_3 b$ value will equal zero in the population, but if the indirect effect is related to $W$, then the resulting $a_3 b$ value will not equal zero.

The created M4 models were used in both studies in this research.

# CHAPTER IV

# M4 MODEL APPLICATION

The applicability of the M4 model was evaluated using empirical data about child developmental psychology among first-grade children from Spain. The M4 model was applied to examine the indirect path from hyperactivity/impulsivity to academic impairment through oppositional defiant behaviors, where the relationship between hyperactivity/impulsivity and oppositional defiant behaviors was moderated by inattention. Figure 3.1 shows the conceptual path model for this application.

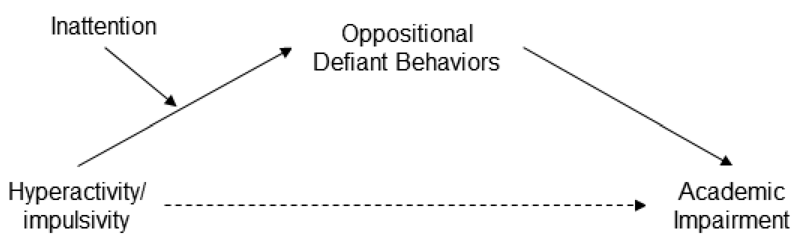


**Figure 3.1**: Conceptual path diagram for M4 model application

Poor academic achievement (i.e., academic impairment) is one of the most prominent outcomes associated with symptoms of attention deficit hyperactivity disorder (ADHD; Frazier, Youngstrom, Glutting, & Watkins, 2007; see also e.g., Barry, Lyman, & Klinger, 2002; Massetti, Lahey, Pelham, Loney, Ehrhardt, Lee, & Kipp, 2008).

However, the process through which symptoms of ADHD impact academic impairment is relatively understudied. Some researchers have hypothesized that study skills or interpersonal skills mediate this relationship (Volpe, DuPaul, DiPerna, Jitendra, Lutz, Tresco, & Junod, 2006). Others have hypothesized that a student's ability to overcome challenges mediates this relationship (Martin, 2014). These studies have been conducted in order to understand the relationship between ADHD and academic impairment. By understanding the intermediary variables, practitioners can determine ways to mitigate negative outcomes.

One possible intermediary variable between ADHD and academic impairment is oppositional defiant behaviors (OD). OD is characterized by argumentative behaviors, resentment, irritability, and anger. The hyperactive/impulsive domain of ADHD (HI) has been shown to predict symptoms of OD (Burns & Walsh, 2002), suggesting that HI influences the development of OD. According to the trait-impulsivity etiological model (Burns, de Moura, Beauchaine, & McBurnett, 2014; see also Beauchaine, Hinshaw, & Pang, 2010) the neurological paths that result in symptoms of HI are expected to develop before the neurological paths that result in symptoms of OD. Furthermore, the neurological paths resulting in the inattention domain of ADHD (IN) are expected to develop before OD in the trait-impulsivity etiological model.

The trait-impulsivity etiological model was used to guide the directional relationship among HI, IN and OD. Specifically, it was hypothesized that the interactive effect of HI and IN would impact OD. Furthermore, it was hypothesized that OD mediated the relationship between HI and AI.[1]

Overall, the primary goal of the application was to address how to apply the M4 model to substantive, real-world data. Although substantive information about the relationships among variables was presented above, this illustration was not meant to inform the literature about the substantive relationships among HI, IN, OD, and AI. Throughout the illustration, relevant pieces of information are presented that should be presented in future applications of the M4 model. How to evaluate and interpret model output as well as how to report relevant results are discussed. This chapter concludes by addressing and answering the research questions based on the application of the M4 model to the empirical data.

## Research Questions

1. How does the M4 model work under non-simulated conditions?
2. How should applied researchers interpret M4 model output?
3. What are some recommendations or guidelines for applied researchers who wish to utilize the M4 model using their own data?

[1] Theoretically IN could have impacted academic impairment, but it was not included as a predictor in order to show first-stage (as opposed to first-stage and direct effect) moderated mediation.

**Dataset for the Illustration**

Data used in this illustration was requested from the owners of the original dataset.

**Sample.** Data were gathered from mother and father reports for first-grade children across 30 elementary schools across the Balearic Islands, and Madrid, Spain. The sample originally contained 1,045 children. Overall, *N* = 798 children had at least partial data relevant to the present project.[2] The original collection of data contained 54% males, and children with an average age of 7 years at the first assessment. Children were not allowed to participate in the original study if they had been diagnosed with a previous learning or behavior disorder. For data relevant to the present study, *n* = 723 mothers and *n* = 603 fathers participated in the study at wave 1, *n* = 603 mothers and *n* = 539 fathers participated in the study at wave 2, and *n* = 502 mothers and *n* = 460 fathers participated in the study at wave 3.

**Measures.** The measures of HI, IN, OD, and AI were evaluated using the Child and Adolescent Disruptive Behavior Inventory Parent Version (Burns & Lee, 2011) across three waves of assessment; data collection included other variables that were not used in the present analysis. Earlier studies on the CADBI had a different number of anchors than presented below (e.g., Burns, Boe, Walsh, Sommers-Flanagan, &

[2] Different analyses show different sample sizes due to missingness as well as the longitudinal aspect of the data.

Teegarden, 2001). The most original scale validation study that included the four relevant constructs assessed a sample of Thai adolescents across four years (Burns, de Moura, Walsh, Desmul, Silpakit, & Sommers-Flanagan, 2008). Reliabilities below are reported from this study.

HI was measured using nine items. One example of an item was “Fidgets with or taps hands or feet or squirms in seat.” Items in this subscale were directly related to ADHD-HI items presented in the DSM-IV. Items were measured on a 6-point Likert scale, where *0 = nearly occurs none of the time (e.g., never or about once per month)*, *1 = seldom occurs (e.g., about once per week)*, *2 = sometimes occurs (e.g., several times per week)*, *3 = often occurs (e.g., about once per day)*, *4 = very often occurs (e.g., several times per day)*, and *5 = nearly occurs all the time (e.g., many times per day)*. It was emphasized that parents should rate these items independently from “oppositional behavior, defiance, anger, hostility or a failure to understand the task or the instructions.” Scale reliability was reported as ranging from .88 to .90 across four years of assessment (Burns et al., 2008).

IN was measured using nine items. An example item was “Has difficulty organizing tasks and activities.” Items in this subscale were directly related to ADHD-IN items presented in the DSM-IV. Items were measured on a 6-point Likert scale, where *0 = nearly occurs none of the time (e.g., never or about once per month)*, *1 = seldom occurs (e.g., about once per week)*, *2 = sometimes occurs (e.g., several times per week)*, *3 = often occurs (e.g., about once per day)*, *4 = very often occurs (e.g., several times per day)*, and *5 = nearly occurs all the time (e.g., many times per day)*. Scale reliability was reported as ranging from .89 to .92 across four years of assessment (Burns et al., 2008).

OD was measured using 16 items. An example item was “Appears angry or resentful toward adults.” Items were measured on a 6-point Likert scale, where *0 = almost never (e.g., never or about once per month)*, *1 = seldom (e.g., about once per week)*, *2 = sometimes (e.g., several times per week)*, *3 = often (e.g., about once per day)*, *4 = very often (e.g., several times per day)*, and *5 = almost always (e.g., many times per day)*. Scale reliability was reported as ranging from .90 to .91 across four years of assessment (Burns et al., 2008).

AI was measured using 4 items. An example item was “Completion of Homework Assignments.” Items were measured on a 7-point Likert scale, where *0 = severe difficulty*, *1 = moderate difficulty*, *2 = slight difficulty*, *3 = average performance for grade level*, *4 = slightly above average*, *5 = moderate above average*, and *6 = excellent performance*. Items were reverse scored so that higher scores indicated greater levels of academic impairment. Scale reliability from was reported as ranging from .83 to .85 across four years of assessment (Burns et al., 2008).

Items for HI, IN, and OD have been previously averaged into three continuous parcels (i.e., indicators; Burns, Servera, Bernad, Carillo, & Geiser, 2014; Preszler, Burns, Litson, Geiser, & Servera, 2016) using an approach by Little et al. (2013). AI was measured by 4 items and two of the items were combined to create 3 indicators. Appendix A shows the relevant items and parcels in the dataset.

**Procedures.** Mothers and fathers independently responded to various questions in a survey about their child’s behavior in the home or community setting. Responses were collected at three waves of assessment. The first wave of data was collected at the end of the spring semester of first grade, the second wave 10 months later, and the third wave 12 months later. All measures were collected at all waves of data collection.

## Considering the Data before Running Analyses

The M4 model was applied to mother and father reports of HI, IN, OD, and AI. It was predicted that OD would mediate the relationship between HI and AI, and that IN would moderate the relationship between HI and OD. This model is an example of a first-stage moderated mediation analysis and was used to examine the M4 approach applied to substantive data.

Before conducting the analyses, many decisions about the data were made. Because there were multiple occasions of measurement, it was decided that the application analysis would include data from multiple times points. All models in the application contain HI and IN as measured at wave 1, OD as measured at wave 2, and AI as measured at wave 3.[3] This does not constitute a strictly longitudinal approach which would require including multiple waves of each construct in the analysis. Due to the complexity of the M4 model already, it was not feasible to examine a model that included all aspects of the M4 model as well as longitudinal aspects without going above and beyond the scope of this project.

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[3] Longitudinally, these constructs have shown relatively high levels of trait consistency across time (Litson, Geiser, Burns, & Servera, 2018 and Preszler, Burns, Litson, Geiser, & Servera, 2017), indicating that a longitudinal measurement structure may or may not add value to the proposed approach.

Additionally, in the present dataset, data were positively skewed. In many applications of this dataset, non-normality was accounted for by using a robust maximum likelihood estimator in M*plus*. However, due to the LMS and bias-corrected bootstrapping procedure used to estimate the M4 models, robust maximum likelihood was not supported alongside these complex iterative and resampling procedures in M*plus*. Fortunately, bootstrap methods account for data non-normality by resampling (e.g., Stine, 1989), and LMS method is robust to moderate violations in data normality (Klein & Moosbrugger, 2000; Cheung & Lau, 2017).

One final consideration before conducting the M4 analyses was to ensure that the means of the latent $X$ and $W$ trait factors were centered at 0 to create an interpretable interaction term. Such was obtained by constraining latent factor means to 0 and estimating all intercepts of the manifest variables.

**A Four-Step Modeling Approach**

The application of the M4 model required four different steps. In the first step, the measurement structure of each construct was empirically evaluated. Single-trait multimethod (STMM) models were applied to IN, HI, OD, and AI, separately. These analyses were primarily used to determine whether the general CT-C($M$ – 1) model was sufficient, or whether indicator-specific trait factors were necessary to appropriately model the multimethod measurement structure for each construct. In the second step, the measurement structure for the combination of all four constructs was evaluated in a single analysis using a multitrait-multimethod, CT-C($M - 1$) model. Furthermore, this step was necessary for creating the common trait factors using the latent means approach. This analysis served as the measurement model underlying the M4 model. Consistency, method-specificity, and reliability were reported from the model output in this step. In the third step, the M4 model without the latent interaction term (i.e., the exclusion of the $XW$ term and the $a_3$ pathway) was evaluated. In the fourth step, the full M4 model shown in Figure 4 was evaluated. The model fit indices from Steps 3 and 4 were compared to determine the significance of including the moderating effect since the LMS approach does not allow estimating global fit statistics. Results were bootstrapped in the final model to evaluate the significance of specific paths and outcomes. At each step, there is a possibility that the model may not fit the data – particularly in Steps 1 and 2. If the measurement portion of the model does not fit the data, researchers should not continue with the M4 modeling approach and instead find a measurement model that fits the data appropriately. Each step and relevant results are discussed in more detail in the following sections.

**Step 1. Determining the STMM measurement structures.** STMM models were first evaluated to determine an appropriate measurement structure for HI, IN, OD, and AI, separately. Fitting these simpler models allowed determining the structure of the data before proceeding with the final analysis. A general STMM model without indicator-specific factors was first evaluated for each construct. Figure 3.1[4] shows an example of this model for HI. Model fit resulted in poor fit for all constructs (see Table 3.1).

Because the STMM models without indicator-specific trait factors did not fit the data well, STMM models with indicator-specific trait factors were evaluated for each construct. Figure 3.3 shows an example of this model for HI. Model fit statistics in Table 3.1 show that the indicator-specific STMM models showed better fit across all constructs. All indicator-specific models showed adequate to excellent fit. Overall, the measurement structure with indicator-specific trait factors fit the data better than the measurement structure with non-indicator-specific trait factors. Indicator-specific trait factors were thus used in all following models.

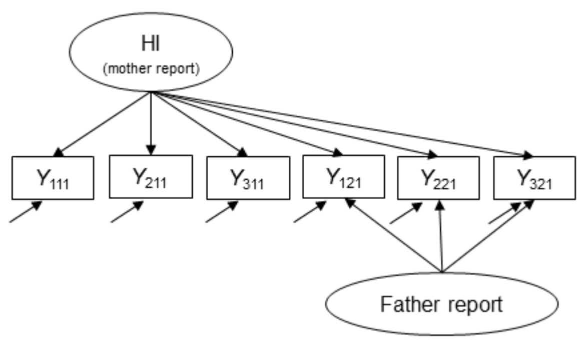


**Figure 3.2**: Single-trait multimethod CT-C(*M*–1) model for HI

[4] M*plus* syntax for all figures in this chapter can be found in Appendix B.

**Table 3.1**. Model fit information for STMM models

| | $\chi^2$ | *df* | *p* | *SF* | RMSEA | CFI | SRMR | AIC | BIC |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Hyperactivity | | | | |
| CT-C($M$ – 1) | 215.01 | 6 | .00 | 1.73 | .22 | .91 | .02 | 8210 | 8307 |
| IS CT-C($M$ – 1) | 2.49 | 3 | .48 | 1.63 | .00 | 1.00 | .01 | 7846 | 7957 |
| | | | | | Inattention | | | | |
| CT-C($M$ – 1) | 126.58 | 6 | .00 | 1.54 | .16 | .96 | .02 | 7255 | 7352 |
| IS CT-C($M$ – 1) | 2.406 | 3 | .49 | 1.35 | .00 | 1.00 | .01 | 7070 | 7181 |
| | | | | | Oppositional Defiant Behaviors | | | | |
| CT-C($M$ – 1) | 158.46 | 6 | .00 | 1.58 | .20 | .94 | .02 | 3109 | 3202 |
| IS CT-C($M$ – 1) | 14.87 | 3 | .00 | 1.45 | .08 | 1.00 | .02 | 2887 | 2993 |
| | | | | | Academic Impairment | | | | |
| CT-C($M$ – 1) | 196.02 | 6 | .00 | 1.83 | .25 | .87 | .05 | 7676 | 7765 |
| IS CT-C($M$ – 1) | 8.47 | 3 | .04 | 0.99 | .06 | 1.00 | .01 | 7331 | 7433 |

*Note*. *df* = degrees of freedom, *SF* = scaling factor for robust maximum likelihood estimator, RMSEA = root mean square error of approximation, CFI = comparative fit index, SRMR = standardized root mean square residual, AIC = Akaike information criteria, BIC = Bayesian information criteria, CT-C($M$ – 1) = correlated traits-correlated (methods – 1) model, IS = indicator-specific.

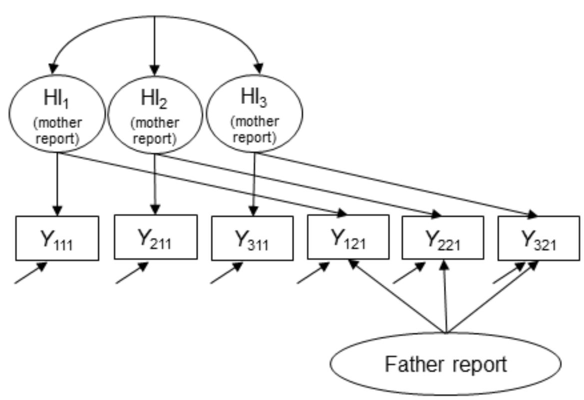


**Figure 3.3**: Single-trait multimethod CT-C($M$ – 1) Model with indicator-specific factors for HI

**Step 2. Determining the MTMM model structure.** In the second step, the measurement structure from the STMM models was evaluated in a single multitrait-multimethod analysis. A CT-C($M-1$) model with indicator-specific factors was fit to the IN, HI, OD, and AI data. This model is shown in Figure 3.4. Fit statistics showed that this model fit the data relatively well, $\chi^2(132, N = 798) = 192.08$, $p = .001$, RMSEA = .024, CFI = .996, SRMR = .013. The CT-C($M-1$) model was the baseline model implemented in the M4 approach.

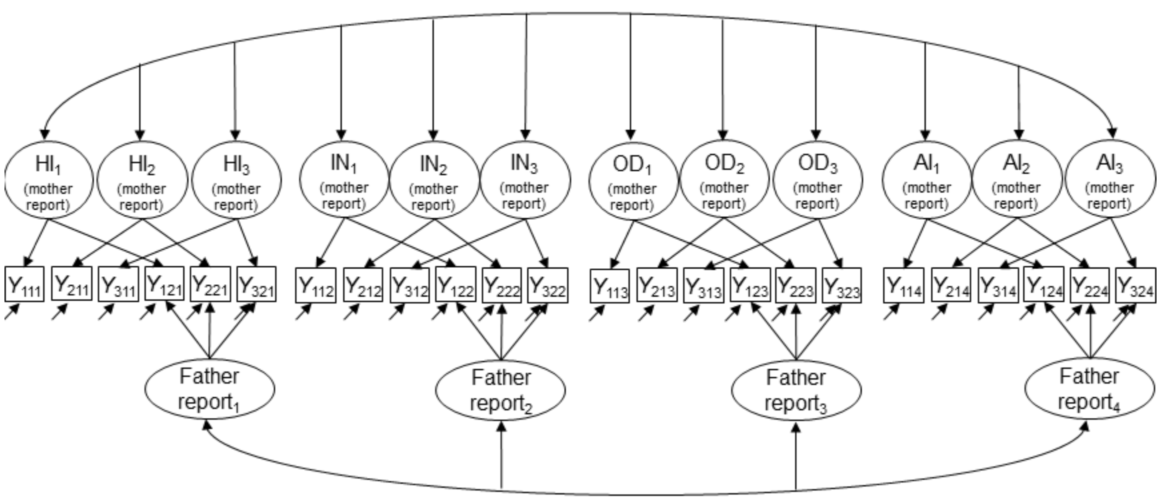


**Figure 3.4**: Indicator-specific MTMM CT-C($M-1$) model for all variables

**Step 2 results. Consistency, method-specificity, and reliability estimates**. Estimates of consistency, method-specificity, and reliability across all constructs were examined (see Figure 3.5). Across constructs, both mother and father reports were quite reliable (range of .81 to .98). Furthermore, fathers showed high shared consistency with mothers (range of .46 to .67), but fathers also showed a moderate amount of unique method-specificity (range of .20 to .43). These results suggest that although mother and father reports shared a relative amount of consistent variance across all constructs, father reports of HI, IN, OD, and AI contained additional method variance that was unshared with mother reports, as shown by the light gray lines in the figure. It was also shown that method-specificity for father reports was lowest among inattention and academic impairment and was highest among oppositional defiant behaviors. Such a result suggests that there was more convergent validity for inattention and academic impairment than oppositional defiant behaviors.

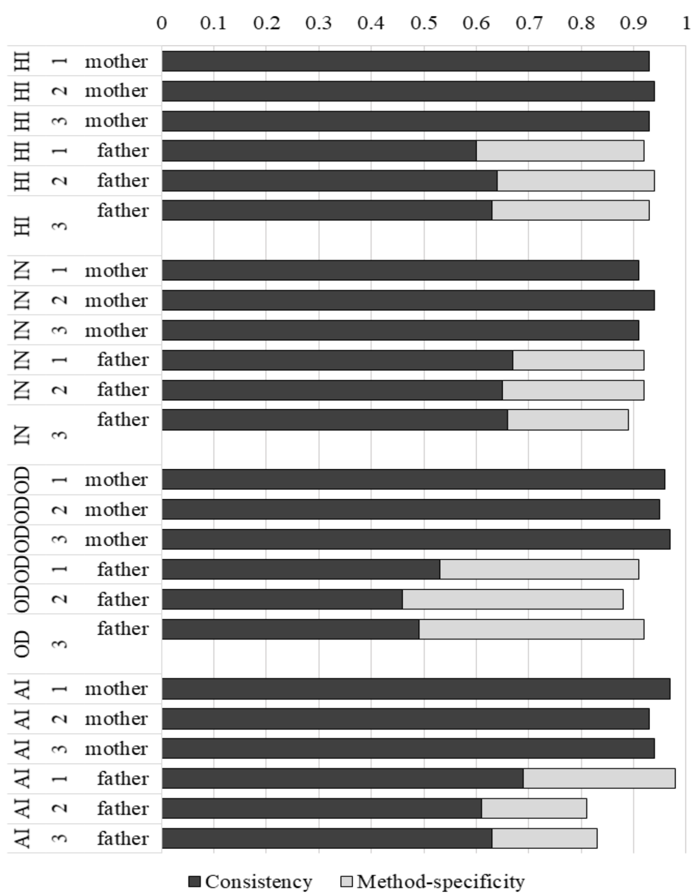


**Figure 3.5**: M4 model consistency, method-specificity, and reliability estimates

**Step 2a. Creating common trait factors using the latent means approach.** As part of the second step, it was necessary to fit a model that included common trait factors as defined by the latent means approach, which was presented in detail in Chapter 3. The indicator-specific latent trait factors were reconstructed into a common trait factor and indicator-specific factors, as shown in Figure 3.5. The latent means approach did not add additional parameters but was instead a second-order reconstruction of the indicator-specific trait factors. Therefore, the model implementing the latent means approach resulted in equivalent model fit as the indicator-specific CT-C($M-1$) model. Model constraints in M*plus* that were necessary to equate the two models included constraining the first-order trait variances to zero and estimating correlations among the second-order common trait and indicator-specific factors.

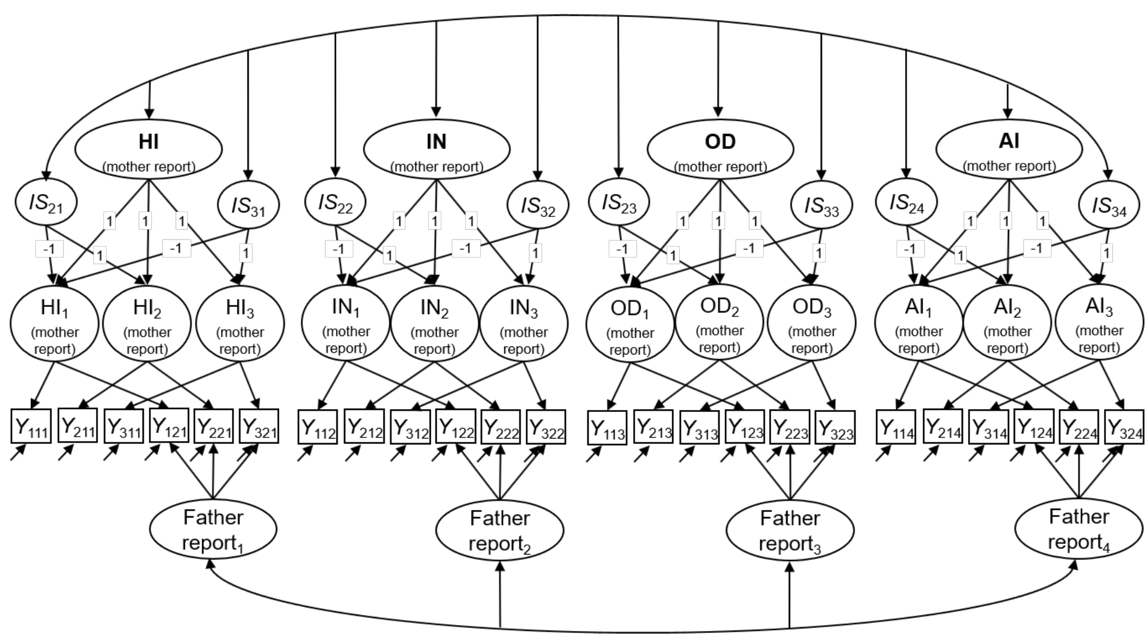


**Figure 3.6**: Latent means reconstruction of the indicator-specific CT-C($M-1$) model

**Step 3. Estimating the M4 model without the latent interaction term.** The CT-C($M$ – 1) model with latent means served as a baseline for creating and interpreting the M4 model. The M4 model was evaluated in two steps. In the Step 3, the M4 model was evaluated without a latent interaction term (see Figure 3.6). Such a model was evaluated because the LMS approach cannot estimate conventional global fit statistics, and the final model using the LMS approach must be compared to a nested model that does estimate global fit indices. The model was initially evaluated without including bias-corrected bootstrap in order to determine model fit. Fit statistics showed that the M4 model without the latent interaction term fit the data well, $\chi^2(133, N = 798) = 221.90$, $p < .001$, RMSEA = .029, CFI = .995, SRMR = .049. The loglikelihood (*LL*) value was also given, *LL* = -12,020.74, and is reported here to evaluate the final model fit in the next step.

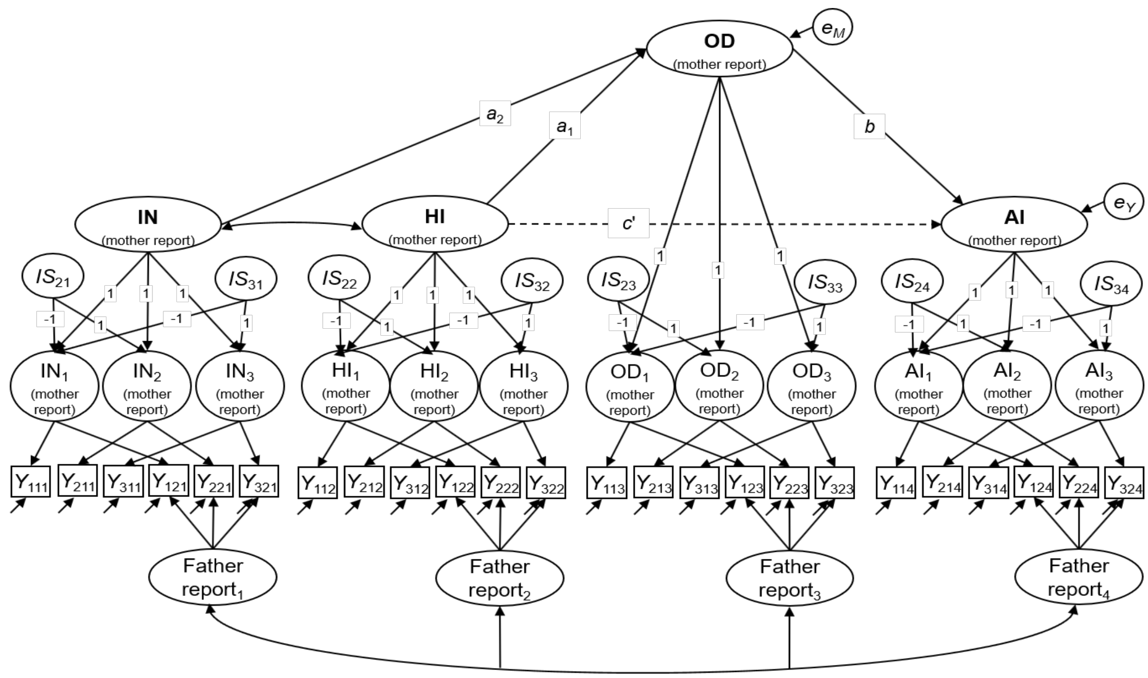


**Figure 3.7**: The M4 model without the latent interaction term

**Step 4. Estimating the M4 model.** In the last step, the full M4 model with the inclusion of the interaction term (*XW*) and the estimated $a_3$ path was evaluated (see Figure 3.7). The interaction term was created using the LMS approach described in Chapter 3. Creation of the interaction term did not affect the fit of the underlying measurement model since the latent interaction term had no mean or variance (Muthén & Asparouhov, 2012; see also Maslowsky, Jager, & Hemken, 2015). The estimation of the $a_3$ path added one additional parameter to the M4 model. The M4 model without the latent interaction term was therefore nested in the full M4 model, indicating that these two models could be compared with an appropriate test of model fit. Because the LMS approach was not used to estimate typical fit indices, the M4 models were compared by evaluating the difference in loglikelihood ($LL_{diff}$) values. The statistical significance of the moderating effect was evaluated by comparing the resulting $2 \times LL_{diff}$ value ($df = 1$) to a chi-square distribution.

**Step 4a. Bootstrap the final results.** The final M4 model from Step 4 was evaluated using 1,000 bias-corrected bootstrap resamples to correct for the asymmetrical distribution of the mediated effect (Bollen & Stine, 1990). The best-practice approach for handling the asymmetric distribution of the indirect effect is to implement bias-corrected bootstrap (MacKinnon, 2008). Bias-corrected bootstrap can be applied to determine the 95% bias-corrected confidence interval (95% BCCI) around the parameter estimate. To show that estimates are different from zero, the 95% BCCI should not pass zero in either direction. Implementing bias-corrected bootstrap into the M4 model resulted in the same fit as the M4 model without bootstrap, as was anticipated.

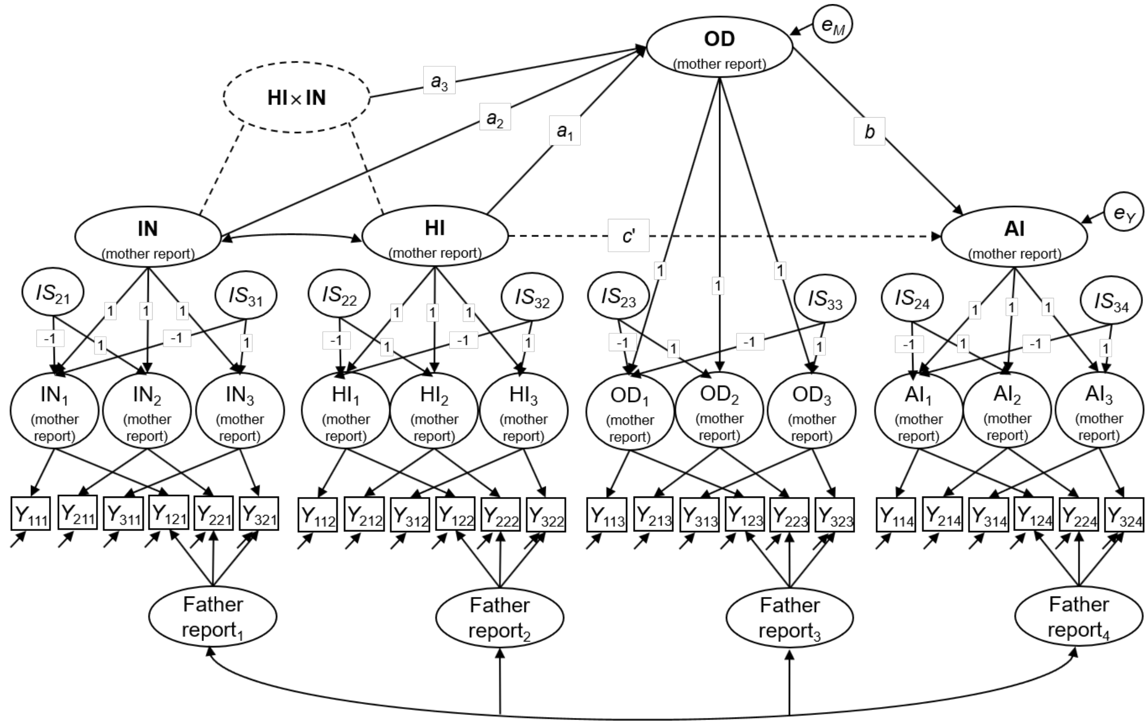


**Figure 3.8**: The M4 model with the latent interaction term

**Step 4 and 4a results. Moderated mediation analysis.** The full M4 model contained 192 free parameters, which was one more parameter than the M4 model without the latent interaction term, thus showing that the only additional parameter estimated was the $a_3$ path. The model fit before bootstrapping showed that *LL* = -12,018.79. When evaluating the difference in fit between the two M4 models, results showed statistical significance, $2 \times LL_{diff}$ = 3.91, *p* = .048. This statistically significant finding demonstrated that the model including the interaction term, *XW*, resulted in a model that did not result in worse fit than the model without the interaction term. In a typical interpretation, the significant difference in model fit would yield the conclusion that IN moderated the indirect effect of HI to AI. However, specific estimates from results were not bootstrapped in this model. Bootstrapping was applied to account for the non-normal distribution of the mediating effect and to determine which specific estimates were statistically significant.

Results from the bootstrapped M4 model revealed a non-significant direct effect between HI and AI, unstandardized[5] $c'$ =.14 [95% BCCI: -.004, .27]. Further, results revealed significant effects for each of the following pathways: OD regressed on HI, $a_1$ = .23 [95% BCCI: .14, .32]; OD regressed on IN, $a_2$ = .13 [95% BCCI = .04, .22]; and AI regressed on OD, $b$ = .28 [95% BCCI: .05, .51]. Results revealed a non-significant effect for the interaction pathway, OD regressed on HI $\times$ IN, $a_3$ = -.04 [95% BCCI: –.11, .02], see Figure 3.9.

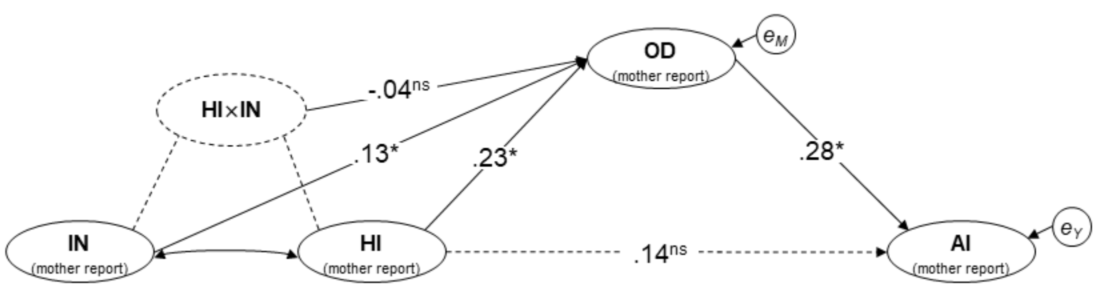


**Figure 3.9:** M4 model moderated mediation results

[5] Because of combining LMS and the bias-corrected bootstrap approach, all results are reported as unstandardized estimates. To standardize estimates, variables would have needed to be standardized before running analyses.

In accordance with the typical interpretation of moderation analysis, a non-significant $a_3$ pathway, such as the result found, would yield the conclusion that IN does not moderate the indirect effect of HI to AI. This conclusion, according to Hayes (2015) is actually incorrect since $a_3$ "does not quantify the relationship between the moderator and the indirect effect" (p. 9), but rather only quantifies the relationship between the moderator and the $a$ pathway. A formal evaluation for testing the effect of the moderator on the indirect effect is to examine the statistical significance of the $a_3b$ pathway since this is the slope of the relationship between the moderating variable, *W*, and the indirect effect. In M*plus*, a new parameter was created to evaluate the Index MM, resulting in an estimate of $a_3b = -.01$ [95% BCCI: –.04, .01]. This result was also not statistically significant. Such a result is a good indicator that inattention did not moderate the indirect effect of hyperactivity on academic impairment through oppositional defiant behaviors.

The question arose about how to interpret the results from this application. The interaction effect significantly improved model fit, but the 95% bias-corrected bootstrap confidence interval of the interaction effect contained zero. According to bootstrapping, the interaction effect was "non-significant," yet according to model fit, the interaction effect was "significant." Although the exact reason for this discrepancy was unknown, it is possible that the model fit criteria had greater power to detect an effect while the bootstrap method had greater Type II error. Or, perhaps the loglikelihood test had a higher rate of Type I error. I chose to interpret bootstrapped results because bootstrapping accounted for the non-normal distribution of the indirect effect. Should other researchers encounter this issue, I would generally recommend interpreting the bootstrapped results and risk potentially committing a Type II error until future research examines this issue in more detail.

If the indirect effect is unrelated to *W*, as in the present case, this is where researchers would stop evaluating further results. Because the present application was for illustrative purposes, I chose to present the results that would be presented if inattention had significantly moderated the indirect effect of hyperactivity on academic impairment through oppositional defiant behaviors.

The indirect effect of *X* on *Y* through *M*, conditional on *W* can be given in the following equation:

$$\begin{aligned} \omega &= a_1 b + a_3 b W \\ &= .23(.28) + (-.04)(.28)W \\ &= .06 - .01W \end{aligned} \tag{39}$$

Substituting relevant values of *W* into the equation resulted in interpretable findings about the conditional indirect effect of *X* on *Y*. Cheung and Lau (2017) as well as Hayes (2013) suggested substituting five values for *W* into this equation: the mean, $\pm 1$ standard deviation, and $\pm 2$ standard deviations. It was possible to calculate these values in M*plus* by creating new parameters under the Model Constraint command. Such allowed estimating the 95% BCCI of each resulting value. Moderated mediation values at the five given levels of the moderator are presented in Table 3.3. These values are the conditional indirect effects. The conditional indirect is greater for children with lower levels of inattention than for children with higher levels of inattention. For example, the indirect effect is .05 for children with inattention levels at +2 SD above the mean, yet the indirect effect is .09 for children with inattention levels at -2 SD below the mean. These results are very small and non-significant. Notably, there was very little change in the indirect effect across levels of the moderating variable. Further, it was also shown that the indirect effect never crossed zero across all levels of the moderator. This indicates a significant indirect effect of HI on AI through OD, regardless of the level of IN.

**Table 3.2**. Moderated mediation effect of X on Y through M across five values of W

| Values | *W* | Effect | $SE_{boot}$ | 95% BCCI |
|---|---|---|---|---|
| *M* + 2 *SD* | 1.95 | .05 | .03 | [.01, .11] |
| *M* + 1 *SD* | .98 | .06 | .03 | [.02, .12] |
| *M* + 0 *SD* | 0 | .07 | .03 | [.02, .13] |
| *M* - 1 *SD* | -.98 | .08 | .03 | [.02, .15] |
| *M* - 2 *SD* | -1.95 | .09 | .04 | [.02, .19] |

*Note*. *M* = mean of *W*; *SD* = standard deviation of *W*; *W* = value of the moderator; Effect = conditional indirect effect (i.e., moderated mediation effect); $SE_{boot}$ = bootstrap standard error; 95% BCCI = 95% bias-corrected bootstrap confidence interval.

When examining the specific moderating results from the M4 model, the *a*-pathways must be interpreted as a set of parameters because of the interaction effect. An example interpretation is, for every one unit increase in HI (holding IN constant), OD increases by .19 (i.e., .23-.04) units. Alternatively, one could state that for every one unit increase in IN (holding HI constant), OD increases by .09 (i.e., .13-.04) units. Importantly, both of these interpretations make clear that the slope between the independent and dependent variable varies as a function of the level of the moderating variable.

**Conclusions**

Overall, results from the application suggest that the relationship between hyperactivity/impulsivity and academic impairment was mediated by oppositional defiant behaviors. Furthermore, the indirect relationship did not vary as a function of inattention. These findings partially support the trait-impulsivity etiological model, which suggests that symptoms of hyperactivity and inattention develop before oppositional defiant behaviors. Although the method used to evaluate data was not strictly longitudinal, results show the hypothesized relationships among variables due to the lagged nature of the dataset. The findings also suggest that OD is an intermediary variable between ADHD symptoms and academic impairment.

Furthermore, findings showed that all constructs contained between 20% and 50% method-specific variance, with oppositional defiant behaviors containing more method-specific variance than hyperactivity, inattention, or academic impairment. Many reasons could explain this finding. Perhaps mothers and fathers interact differently with children; perhaps children behave differently around their fathers as compared to mothers; perhaps certain behaviors are more or less acceptable according to different parents. Overall, the presence of method effects showed the necessity of modeling the data using a multimethod measurement structure.

Although the substantive results were interesting, the objective of this chapter was to examine the applicability of the M4 model under non-simulated conditions. The M4 model performed well in the application. In response to the first research question, *how does the M4 model work under non-simulated conditions?* The M4 model showed proper convergence and no improper parameter estimates in the present approach and resulted in interpretable findings. One concern about the present modeling approach was the contradictory findings about the presence of the moderated effect. A test of model fit indicated that a model including the moderated path fit no worse than a model without the moderated path. However, results from the 95% BCCI showed that the moderated path was nonsignificant. Future research could explore this possibility of discrepant findings across model fit and BCCI estimates in more depth. Specifically, future research should examine whether a simple loglikelihood test is adequate for detecting the moderated effect in the presence of mediation analysis.

In response to the second research question, *how should applied researchers interpret M4 model output?* In the application above, basic interpretations were applied to important findings to evaluate from the M4 model. Important findings to report include trait consistency, method-specificity, and reliability, as well as the indirect effect across different levels of the moderating variable.

In response to the third research question, *what are some recommendations or guidelines for applied researchers who wish to utilize this model using their own data?* It was recommended to use a four-step approach to evaluate the M4 model. The application began by evaluating simple, single-trait models and became more complex with each step. It is possible that the M4 model is not appropriate for specific types of data, and such can be determined by evaluating model fit in accordance with theory at different steps. In Step 1, if each of the variables does not have multimethod data structure, then the M4 approach should not be attempted.[6] In Step 2, if the combined MTMM measurement model does not fit the data according to model fit criteria, then the M4 approach should not be attempted. Estimation and model fit issues should not occur in Steps 3 and 4 as long as the models in Steps 1 and 2 fit the data.

Only the model in the final step was estimated using bootstrapping methods. Evaluating all models using bootstrapping methods can be time-consuming and was unnecessary for determining the best model fit. One recommendation for successfully applying the M4 model to applied data is to avoid using bias-corrected bootstrap until the final step of the analysis. The approach could become very complex very fast because both measurement and structural portions are included in the M4 model. It is recommended to follow each step from this application closely, taking care to find an appropriate STMM measurement structure before running the more complex CT-C($M$ – 1) and M4 models. Furthermore, because of many default settings in M*plus*, there were various model constraints necessary for proper model identification which were outlined in the provided Appendix B. It is therefore recommended to use the syntax provided in Appendix B to facilitate applying M4 models to one's own data. Each model in this appendix corresponds to the figures presented throughout this application.

One caution about evaluating the M4 model is to remain aware of computing time. In the present application, the M4 model with only two methods and three

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[6] It may be possible to examine the M4 model when multimethod data are not present for each variable. However, this has not yet been evaluated and researchers should exercise caution evaluating such models.

indicators assessed with bias-corrected bootstrap required 18 hours to converge. Using only the LMS approach without bias-corrected bootstrap, the same model took only two minutes to converge. While these times may vary across different computers, the additional time necessary to use bias-corrected bootstrap was substantial. Since bias-corrected bootstrap does not affect model fit, it is imperative to determine whether the full M4 model fits better than the M4 model without the latent interaction term before bootstrapping the results.

# CHAPTER V

# MONTE CARLO SIMULATION STUDY OF THE M4 MODEL

New, complex models, such as the M4 model, must be scrutinized for their performance under various conditions to determine under which conditions the model performs well versus poorly. Such conditions may include sample size, population parameters, and missingness, to name a few. For example, an important question is, which sample size is required for the model to return appropriate parameter estimates and standard errors. Performance may be evaluated based on whether sample estimates are biased, whether the model converges, whether the model gives improper parameter estimates (e.g., a correlation exceeding 1.0), or whether specific effects have adequate power.

A common research design in quantitative psychology to evaluate the performance of complex models is called a Monte Carlo simulation design. Monte Carlo simulations, by design, are random experiments in which researchers set up population models, draw random samples from the population, and examine the performance of statistical modeling approaches (Muthén & Muthén, 2002). Paxton, Curran, Bollen, Kirby, and Chen (2001) proposed guidelines for conducting Monte Carlo simulation designs in psychology using a nine step approach: 1) develop a research question using theory, 2) create a theoretically driven model, 3) design experimental conditions with which to test the model, 4) determine the values of population parameters, 5) choose a software package with which to carry out the simulation design, 6) execute the simulation, 7) store files in a safe, protected environment, 8) verify the study results, 9) summarize and report results. To plan the Monte Carlo simulation, I followed these nine steps.

The objective of the present simulation study was to examine the M4 model in a relatively limited number of circumstances likely to be found in real world situations. Namely, four conditions were varied, including sample size, different levels of method-specificity, correlations among method factors, and fitting a misspecified model to the data. To ensure the present simulation study was relevant to current, applied research, parameters relevant to the structural portion of the M4 model as well as sample size were obtained using a meta-analytic literature review.

This chapter is therefore organized into two sections. In the first part of this chapter, a meta-analytic literature review is discussed and results from the review are presented. In the second half of the chapter, findings from the Monte Carlo simulation study are presented and discussed.

## Research Questions

1. Under which and how many simulated conditions does the M4 model:
    a. Have adequate power to detect the mediated and moderated effects?
    b. Produce biased estimates or standard errors of the mediated or moderated effects?

2. Under which and how many simulated conditions does a misspecified model (i.e., the M4 model without method factors, equivalent to a latent variable moderated mediation model [LVMM]; Cheung & Lau, 2017):
    a. Have adequate power to detect the mediated and moderated effects?
    b. Produce biased estimates or standard errors of the mediated or moderated effects?
3. Which conditions produce higher instances of:
    a. Non-converged solutions?
    b. Low parameter coverage for the moderated mediation population parameters?

**Meta-Analytic Review to Determine Moderated Mediation Population Parameters**

A literature review of studies which use moderated mediation analysis within the fields of clinical psychology, developmental psychology, and prevention science was conducted to determine the most appropriate population parameter values for the mediated and moderated pathways. Multimethod designs within moderated mediation analysis were also examined. Peer reviewed articles were originally included in the literature review if they 1) reported findings from a moderated mediation analysis, 2) were published after 2013,[7] and 3) reported results directly related to the advancement of knowledge in one of the three given topic areas.

One broad search was conducted and articles were included and excluded accordingly. A search of the PsychINFO database using the search term ("moderated mediation" OR "conditional process analysis") AND ("development" OR "prevention science" OR "clinical psychology") resulted in 213 articles. Articles were published between 2013 and January of 2018. A brief review of titles and abstracts found that 140 articles met the basic inclusion criteria.

This literature review was not intended to be a comprehensive review of all literature pertaining to moderated mediation in clinical psychology, developmental psychology, or prevention science fields and various exclusion criteria were established to remove articles. The first five criteria were established before coding articles. The last five criteria were established due to necessity during the coding of articles. Articles were excluded if they:

1. were not written in English ($n$ = 9),
2. contained only categorical moderating variables ($n$ = 47),
3. contained moderating variables that did not interact with the *a*-pathway ($n$ = 26),
4. were not related to one of the three areas of research ($n$ = 7)
5. were duplicates and/or addendums ($n$ = 1)

[7] The year 2013 was chosen because this is the year the first-edition of the book, *Introduction to Mediation, Moderation, and Conditional Process Analysis* by Andrew Hayes was published.

6. did not actually evaluate moderated mediation; e.g., the authors called the analysis moderated mediation but only conducted moderation ($n$ = 7)
7. did not specify with which path the moderator interacted ($n$ = 1)
8. contained overly complex models that were not comparable to other articles ($n$ = 1)
9. were theoretical methods articles and did not include an application of moderated mediation ($n$ = 1)
10. failed to report estimates or necessary information to calculate standardized estimates for the pathways of interest ($n$ = 9)

The total number of articles included in the literature review was $N$ = 30 (references and corresponding ID numbers for these articles can be found in Appendix C). On average, each article contained three pathways from $X$ to $Y$ through $M$ moderated by $W$ that were included in the coding process. A total of 85 pathways of moderated mediation were included in the present review. Each different pathway within each article was quantified according to the coding scheme found in Table 4.1. Four areas of information were coded: general article information (e.g., the relevant area of research), study design (e.g., whether the study was longitudinal), data characteristics (e.g., the sample size), and standardized study results (e.g., the standardized $b$ pathway). These results were used to inform the population parameters in the simulation design.

**Table 4.1**: Coding Scheme for Literature Review

| Variable of Interest | Value | Value names or representation |
|---|---|---|
| General Article Information | | |
| Year of publication | [input] | NUMERICAL VALUE |
| Area of research | 1 | Developmental psychology |
| | 2 | Prevention science |
| | 3 | Clinical psychology |
| Study Design | | |
| X variable name | [input] | TEXT INPUT |
| M variable name | [input] | TEXT INPUT |
| Y variable name | [input] | TEXT INPUT |
| W variable name | [input] | TEXT INPUT |
| Pathway(s) moderator influences | 1 | *a* |
| | 2 | *b* |
| | 3 | *c′* |
| Moderated mediation approach | [input] | TEXT INPUT |
| Longitudinal design | 0 | No |
| | 1 | Pseudo |
| | 2 | Yes |
| Method(s) of data collection | 1 | Self-report |
| | 2 | Other report |
| | 3 | Clinical interview |
| | 4 | Physical assessment |
| | 5 | Other |
| Multimethod measurement on X, M, W, or Y | 0 | No |
| | 1 | Yes |
| Data Characteristics | | |
| Sample size | [input] | NUMERICAL VALUE |
| Level of missingness | [input] | NUMERICAL VALUE |
| How were MM handled? | 0 | Not applicable |
| | 1 | Averaged |
| | 2 | Methods switch across X, M, W, and Y |
| | 3 | One model per method |
| | 4 | Other |
| | 5 | Unclear |
| Were latent variables used? | 0 | No |
| | 1 | Yes |
| Standardized Results | | |
| $a_1$ , $a_2$, $a_3$, $b$, $c'$ | [input] | NUMERICAL VALUE |
| Significance $a_1$ , $a_2$, $a_3$, $b$, $c'$ | 0 | No |
| | 1 | Yes |

**Results from the Literature Review**

Results showed that articles were represented across all years included in the literature review. Three articles were from 2013, one from 2014, 10 from 2015, eight from 2016, 7 from 2017, and one published early in 2018. Articles were representative across developmental (*n* = 11), prevention science (*n* = 17), and clinical (*n* = 12) applications. The sum of these values is greater than the number of articles because some articles were deemed representative of more than one field.

***X*, *M*, *W*, and *Y* variables**. Appendix D shows the 85 different *X*, *M*, *Y*, and *W* variable combinations found in included articles. Each variable was post-hoc coded as negative (e.g., depression, victimization, belittling), positive (e.g., social support, satisfaction, psychological well-being), or neutral (e.g., self-awareness, gender non-conformity, intervention condition). Results showed that *X*, *M* and *Y* contained more negative constructs (*n* = 51, 51, 43, respectively) than neutral constructs (*n* = 27, 26, 22, respectively), and the fewest positive constructs (*n* = 7, 8, 20, respectively). Conversely, *W* contained the most positive constructs (*n* = 42), fewer neutral constructs (*n* = 24), and the least negative constructs (*n* = 19). No specific constructs or variable combinations seemed to be used more often than others, indicating that moderated mediation analysis has been used to examine a large variety of relationships among variables.

**Moderated mediation approach**. To examine moderated mediation, 17 out of 30 articles used the SPSS macro, PROCESS (Hayes, 2013; Hayes, 2017) and followed steps outlined in Hayes (2013) book.[8] Other approaches to examine moderated mediation included using regression methods ($n = 4$), a path model ($n = 3$), or Bayesian analysis ($n = 2$). Of the remaining $n = 4$ articles, one used an autoregressive model, another used a multilevel mediation model, another used a latent variable moderated mediation model, and one did not clearly specify how moderated mediation was examined. Most articles also used bootstrapping methods to handle the asymmetrical distribution of the indirect effect ($n = 23$). Three articles did not specify how they handled the asymmetrical distribution of the indirect effect. The remaining four articles used different approaches to handle the asymmetrical distribution of the indirect effect, with one using the Satorra-Bentler correction, another using robust standard errors, one using an extended Johnson-Neyman approach which is appropriate for moderation but unclear in its application to mediation analysis, and another not clearly defining how they examined the moderated-mediated effect. In sum, most articles used regression or path-based approaches in combination with bootstrapping methods to evaluate moderated mediation models. Bootstrapping is best-practice for mediation analysis, so finding that researchers used bootstrapping methods to evaluate moderated mediation results was a promising finding.

**Longitudinal design**. Most studies ($n = 20$) did not use longitudinal methods to examine moderated mediation analysis. Only $n = 3$ studies used longitudinal methods to evaluate moderated mediation models. An additional $n = 7$ studies used cross-sectional methods with longitudinal data, meaning they measured variables across time, but did not

[8] A new version of this book is in print (Hayes, 2017).

account for time in the moderated mediation analysis. The M4 model is currently, by design, a cross-sectional model and is therefore already aligned with many researchers' approaches. While longitudinal approaches to moderated mediation models allow making conclusions about time precedence, they are not strictly necessary to examine relationships among variables as long as results are interpreted in accordance with the research design.

**Methods of data collection and multimethod measurement**. Self-report was used in every study included in the literature review. Many studies used self-report as the only method of data collection ($n$ = 20) while some studies used self-report plus at least one other method ($n$ = 10). Of all other methods aside from self-report, other report was the most common method of data collection ($n$ = 7), followed by "other" (e.g., observations that were recorded and coded) ($n$ = 5), and physical assessment ($n$ = 2). Of the 10 studies that used multiple methods to gather data, only $n$ = 3 studies used multimethod assessment to gather data on a single construct.

**Sample size**. Overall, sample size was found to be quite variable. The largest sample consisted of $N$ = 5,374 individuals while the smallest sample consisted of only $N$ = 91 individuals. The average sample size across studies was 854 with a standard deviation of 1,166. Due to extreme outliers with very large sample sizes, it was also informative to examine the median sample size. The median sample size was 379. Values close to the mean and median were included in the Monte Carlo simulation as population parameters. Additionally, a smaller sample size of 200 was chosen as well.

**Missingness**. Missingness was not often reported in studies (*n* = 20). When missingness was reported, it ranged from 1% to 34% of the sample. Missingness, when reported, was used in the present study to estimate more accurate sample sizes. The ways in which individual studies dealt with missing data was not coded.

**How were multiple methods handled?** Most studies that included multiple methods of gathering data used different methods to measure different constructs (*n* = 7). Only *n* = 3 articles used multimethod assessments within constructs. In one article (Baardstu, Karevold, & von Soest, 2017), it was unclear how multiple methods were combined or utilized. In a second article (Bunford et al., 2015), parent- and self-report methods were averaged for one variable used in analysis. In a third article (Brock et al., 2015), a moderated mediation path analysis was examined separately for mother report and clinician report.

**Were latent variables used?** Few studies (*n* = 4) used latent variables to examine moderated mediation. Of these four studies, only one used latent variables for all constructs. This specific study (Racine & Martin, 2017) followed the latent variable moderated mediation approach introduced by Cheung and Lau (2017). Two studies used latent variables for the dependent *Y* factor, and one study used latent variables for the *X*, *M*, and *W* factors.

**Standardized results.** Standardized results were coded for the different pathways in the moderated mediation model. In the review, only *n* = 13 articles (or *n* = 40 pathways of moderated mediation) reported standardized effects. For the 17 articles that did not report standardized effects, a standardized effect (i.e., a standardized regression coefficient or partial correlation) was calculated using information obtained from articles.

***Standardizing unstandardized pathways***. A total of $n = 17$ articles (or $n = 45$ pathways of moderated mediation) in the literature review did not report standardized effects in their results. Correlation matrices and standard deviations of the raw variables were originally intended to be used as the primary source for calculating standardized effects. However, this approach was not possible due to the lack of reporting correlations between the interaction term *XW* and other variables (e.g., *M*). Instead, unstandardized coefficients, standard errors, *p*-values, and reported *t*-test statistic values were used in various ways to calculate standardized effects.

If a *t*-test statistic was reported, the approach for calculating the standardized regression coefficient was simple. The *t*-test for a regression coefficient is:

$$t = r\sqrt{\frac{n-2}{1-r^2}} \tag{40}$$

where $t$ = the *t*-test value, $n$ = the sample size for the analysis, and $r$ = the standardized regression coefficient. Equation 40 only uses three estimates: $t$, $r$, and $n$. Solving for $r$, Equation 35 was transformed to:

$$r = \sqrt{\frac{t^2}{t^2 + n - 2}} \tag{41}$$

Equation 36 was used to calculate *r* whenever a *t*-value was reported. If sample size for the specific analysis was not reported, sample size was assumed equal to the *N* reported in the methods section, multiplied by 1 – missingness to control for missing values.

Some articles did not report *t*-values in their results. When *t* was not reported, the equation $t = B / SE$ was used, where *B* was the unstandardized effect and *SE* was the standard error of the unstandardized effect. Equation 41 was then used to calculate *r*. If *SE* was not reported in conjunction with the unstandardized effect, the exact *p*-value was used to estimate the value of *t* using an inverse function calculated on Microsoft Excel (this was done for three estimates in one article, and two estimates in a second article). Estimating a *t*-value from a *p*-value was preferable to not estimating a *t*-value.

When the standardized effect was not reported, the exact *p*-value was not reported, the *t*-value was not reported, and/or a standard error was not reported alongside an unstandardized effect, effects could not be standardized, and the article was removed from the review. A total of 9 articles fell under this criterion. These nine articles were not part of the 30 articles included in the literature review. It is important to mention that these articles did not report other information, such as confidence intervals, that could have been used to "estimate" an effect size.

All 85 effect sizes within each article are presented in Appendix D, alongside article ID, sample size, and level of missingness. This table of effects was used to determine appropriate population parameters for the $a_1$, $a_2$, $a_3$, *b*, and $c'$ pathways for the simulation study.

**Determining population parameters for $a_1$, $a_2$, $a_3$, $b$, and $c'$.** The goal of the literature review was to identify appropriate population values for the $a_1$, $a_2$, $a_3$, $b$, and $c'$ parameters. Due to the hierarchical nature of the meta-analytic data where effects were nested within articles, multilevel models were used to determine appropriate effect size estimates for each parameter. A multilevel model can appropriately account for variance due to nesting and was ideal for the current study because some articles contained many effect sizes per parameter while other articles contained only one effect size per parameter. A simple random intercept model was evaluated for each parameter, separately. Analyses were conducted in R using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015).

To calculate appropriate values for the $a_1$, $a_2$, $a_3$, $b$, and $c'$ parameters to be used in the Monte Carlo simulation study, each effect size estimate was first recoded as an absolute value in order to avoid obtaining zero effects due to positive and negative path coefficients. Only statistically significant effects were examined, as recommended by Paxton and colleagues (2001). Each multilevel model was fit using maximum likelihood estimation.

Table 4.2 shows results from the multilevel analyses. Presented effects include the mean effect size value which was equal to the intercept estimate in the multilevel model, the standard error of the effect size value, the number of significant effects for the parameter, the number of articles containing significant effects for the parameter, and the intraclass correlation. Notably, the average effect size estimate for all paths across articles was rather small, ranging from .15 to .28. When compared to the standard effect size estimates commonly used in complex mediation Monte Carlo simulation studies (e.g., Thoemmes, MacKinnon, & Reiser, 2010), the effects from the review lie between small (.14) and medium (.36) effect sizes. These mean values were used as population values in the Monte Carlo simulation study.

**Table 4.2**: Results from the Multilevel Models Estimating Effect Sizes

| Parameter | $M_{es}$ | $SE_{es}$ | $n_{effects}$ | $n_{articles}$ | *ICC* |
|---|---|---|---|---|---|
| $a_1$ | .275 | .030 | 51 | 24 | .824 |
| $a_2$ | .255 | .043 | 44 | 16 | .869 |
| $a_3$ | .147 | .014 | 37 | 25 | .963 |
| $b$ | .235 | .028 | 61 | 25 | .899 |
| $c'$ | .196 | .027 | 34 | 15 | .961 |

*Note*. $M_{es}$ = the mean effect size estimate; $SE_{es}$ = the standard error of the effect size estimate, $n_{effects}$ = number of statistically significant effects per parameter, $n_{articles}$ = number of articles containing at least one statistically significant effect, *ICC* = intraclass correlation coefficient

**Monte Carlo Simulation Study**

Chapter III presented two M4 models, one with and one without indicator-specific trait factors. When simulating data, the use of indicator-specific trait factors added noise that unnecessarily complicated the calculation of simulation model parameters. In order to simplify the simulation design void of unnecessary noise, indicator-specific trait factors were not included in the simulation design. The model used to generate population data was the M4 model with (non-indicator-specific) general trait factors, as was shown in Figure 2.4. The model is again shown in Figure 4.1 with the relevant population parameter values for the simulation design, which are discussed below.

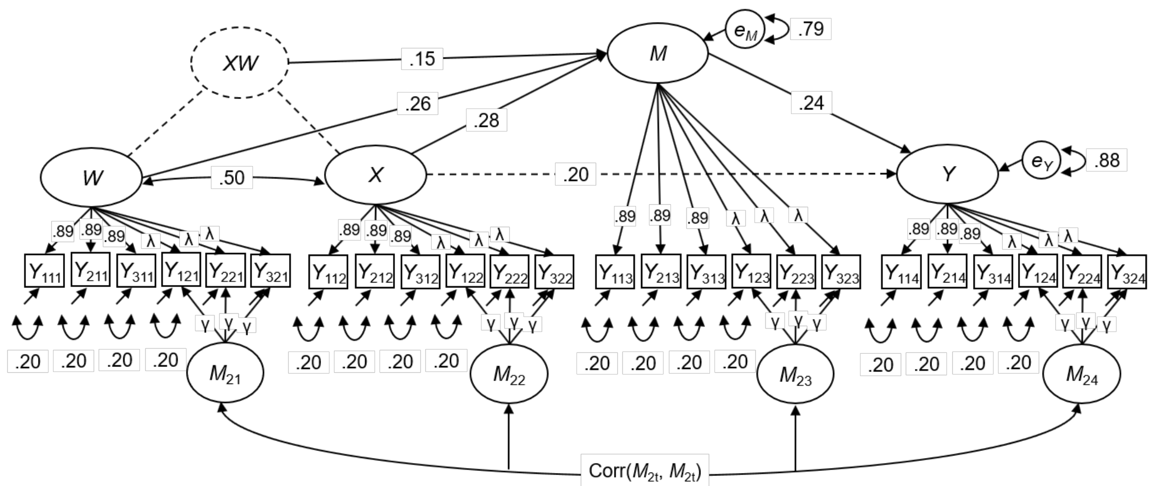


**Figure 4.1**: M4 model with population parameter values for the Monte Carlo simulation

**Monte Carlo population parameter values and experimental conditions.** A total of 36 cells were examined in the Monte Carlo simulation study. Sample size, method-specificity, and strength of the correlation among method factors were all varied. Each condition was evaluated across two sample models: a correctly specified M4 model and an incorrectly specified M4 model. The simulation design was fully crossed.

Parameters that were not varied had fixed effects across all conditions. The $a_1$, $a_2$, $a_3$, $b$, and $c'$ pathways were assigned population parameter values of .28, .26, .15, .24, and .20 from the literature review earlier in this chapter. Population values for variances, relevant covariances, and factor loadings are shown in Figure 4.1. All indicators had a set reliability of .80 indicated by setting all error variances to .20 and trait factor loadings for the reference method to .89. The correlation between *X* and *W* was set to .50. All latent trait and method factors were normally distributed with a mean of 0.0 and variance of 1.0, not shown in the figure. In order to set all trait factor variances equal to 1.0, the residual variances for the dependent latent factors, *M* and *Y*, were determined using covariance algebra. Appendix E shows the covariance algebra used to solve for the *M* and *Y* residual variances.

The sample size in the Monte Carlo simulation had three possible values: 200, 400, or 850. The value 850 was chosen because it was close to the mean sample size found in the literature review discussed earlier in this chapter. The value 400 was chosen because it was close to the median sample size found in the literature review. The value 200 was chosen to examine a smaller sample size that may be more realistic for certain applications.

Method-specificity (i.e., the amount of variance in the observed score due to the method factor) had three possible values: low method-specificity $Mspe(Y_{imt}) = .16$, moderate method-specificity $Mspe(Y_{imt}) = .40$, and high method-specificity $Mspe(Y_{imt}) = .64$. These values were chosen because they represented conditions where the relative percentage of true score variance due to method effects was 20%, 50%, and 80%, respectively. To vary the proportion of method-specificity, trait factor loadings, $\lambda_{imt}$, and method factor loadings, $\gamma_{imt}$, were varied. Factor loadings specific to the reference method $\lambda_{i1t}$ were not varied which resulted in consistency equaling reliability for the reference method; only non-reference method factor loadings were varied in the simulation design. Values for the factor loadings as they corresponded to the proportion of method-specificity conditions are given in Table 4.3. The algebra and covariance algebra used to determine these values can be found in Appendix F.

**Table 4.3**: Factor Loading Estimates for the Three Method-Specificity Conditions

| Simulation Condition | | | | Factor Loadings | | |
|---|---|---|---|---|---|---|
| $Mspe(Y_{imt})$ | $Mspe(\tau_{imt})$ | $Con(Y_{imt})$ | $Con(\tau_{imt})$ | $\lambda_{imt}$ | $\gamma_{imt}$ | $\lambda_{i1t}$ |
| .16 | .20 | .64 | .80 | .80 | .40 | .89 |
| .40 | .50 | .40 | .50 | .63 | .63 | .89 |
| .64 | .80 | .16 | .20 | .40 | .80 | .89 |

Strength of the correlation among method factors varied across two conditions: low correlation (.2) or moderate correlation (.5). These values were chosen because they were similar to the range of correlation values found in the application of the M4 model. The value .20 represents weak to moderate correlations among method factors, indicating that method factors shared some (but not too much) variance across traits. The value .50 represented a relatively large correlation among method factors, indicating that method factors shared a substantial amount of variance across traits.

Two sample models were fit to each of the 18 (3 sample sizes $\times$ 3 levels of method-specificity $\times$ 2 correlation among method factor) simulation conditions. The M4 model was first fit to each of the simulation conditions. Next, a misspecified M4 model that purposefully excluded method factors (i.e., a latent variable moderated mediation [LVMM] model) was fit to each of the simulation conditions. The rationale for examining the model without method factors was to determine what bias emerged when method effects were present but method factors were excluded from the model.

Parameters that were not evaluated in the literature review nor specified above (e.g., the correlation allowed between the trait and method factors not pertaining to the trait, intercept values), were given values based on the application from Chapter IV. Population values for all fixed parameters can be found in the simulation M*plus* syntax in Appendix G.

Although bootstrapping methods were originally intended to be included in the study, they were ultimately removed from the simulation study. The bias-corrected bootstrap method is computationally intensive, especially combined with other approaches that require resampling or iterative processes such as LMS.[9] Because the present approach required using LMS, it was necessary to reduce the required computational time. The rationale behind removing bootstrapping from the study was that if LMS could handle non-normal distributions due to the creation of the interaction term, it may be suited to handle the non-normal distributions of the indirect effect. Such was examined throughout the course of the simulation design.

The simulation study was conducted using M*plus*, primarily versions 8 and 8.1 (Muthén & Muthén, 1998-2017). The University of Utah Center for High Performance Computing (2016) was used as needed to run the simulation analysis. MplusAutomation

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[9] A test model using only 10 bootstrapped samples with only 100 Monte Carlo replications took nearly 25 hours to run on the most high-powered computer available to me. Multiplying this by 500 (100 times the number of bootstrap samples and 5 times the number of Monte Carlo replications) would have resulted in each cell of the simulation taking more than one year to run.

(Hallquist & Wiley, 2015), a package in R, was used to read and create a dataset from the results of the simulation study. Data were stored in an online, protected cloud account (i.e., Box). All files were named following a previously created naming schema to maintain organization of the files, and all files from the simulation were saved and will continue to be saved for at least one year following the completion of the project.

Once the final simulation was ready, file size and output were visually examined to check that each condition correctly ran, and empirical results were evaluated alongside theory. Five-hundred replications (Paxton et al., 2001) were specified within each cell of the simulation. Each cell of the simulation took between four and twelve hours to run.

Results were examined across seven moderation and mediation parameters: the $a_1$, $a_2$, $a_3$, $b$, and $c'$ paths, the Index MM, and the indirect effect. For each of these parameters, results were examined for 1) convergence issues, 2) the statistical power to detect significant effects, 3) relative bias of both the parameter estimate and the standard error estimate, and 4) conditions which resulted in low parameter coverage. Convergence issues were examined as the proportion of solutions per condition that did not converge. Statistical power was evaluated as the proportion of times that a non-zero effect was statistically significant. Parameters that did not meet or surpass power of .80 were considered underpowered while results that surpassed power of .80 were deemed satisfactory. Relative bias was calculated as the difference between the effect estimate and the true population parameter, divided by the true population parameter value. Unbiased parameter estimates exhibit relative bias values less than .10 while unbiased standard error estimates exhibit relative bias values less than .05. Parameter coverage rates between .91 and .98 were considered satisfactory. These criterion values are the same as those proposed by Muthén and Muthén (2002).

## Simulation Results

**Convergence**. When the M4 model was correctly specified, models converged almost perfectly across conditions. Only one replication in the condition where sample size equaled 400, method variance equaled .20, and method correlation equaled .20 did not converge; 499 replications in this condition did converge. Even when models were misspecified (e.g., when they did not include a method factor), models converged, on average, 98.6% of the time. Convergence was not an issue for the M4 model.

**Parameter bias**. Relative parameter bias of each parameter of interest was calculated by subtracting the population estimate from the observed estimate and dividing by the population estimate. The recommended maximum value for parameter bias was .10 (Muthén & Muthén, 2002). Results for parameter bias were quite clear; using the LVMM model when the M4 model was the correct population model resulted in biased parameter estimates (see Table 4.4). The most egregious condition that resulted in unsatisfactory levels of parameter bias was using the LVMM model when method-specificity was equal to .5 (i.e., when half of the true score variance is due to true trait variance while the other half is due to true method variance). Average parameter bias for

$a_1$ (bias = .32), $a_3$ (bias = -.27), $c'$ (bias = .45), Index MM (bias = -.22), and the indirect effect (bias = .44) was obvious among all cells containing this condition. Parameter bias was less pronounced when method-specificity = .2 (bias range: .05 to .26) or when method-specificity = .8 (bias range: .04 to .19). For correctly specified conditions (the M4 conditions), results across all parameters were unbiased (bias range: -.03 to .04). Most interesting, the $a_3$ parameter and Index MM contained almost no parameter bias. The indirect effect was slightly positively biased (range: .03 to .04) but not biased enough to be of concern.

**Standard error bias.** Relative standard error bias of each parameter of interest was calculated by subtracting the standard error population estimate from the observed estimate and dividing by the population estimate. The recommended maximum value for standard error was .05 (Muthén & Muthén, 2002). Standard error estimates were similarly biased like the parameter estimates. Like parameter bias, standard error bias was worse for the LVMM condition compared to the M4 condition (see Table 4.5). Unlike parameter bias, sample sizes of 400 in the M4 condition resulted in standard error bias for the $c'$ pathway and, in one instance, bias for the *b* pathway. Neither the indirect effect nor the Index MM contained biased standard errors when the M4 model was the sample model. Such a result may indicate that the LMS approach need not be combined with bias-corrected bootstrapping methods in order to obtain adequate standard error estimates in latent variable moderated mediation analysis. However, given the relatively few conditions examined in the present simulation, this result should be interpreted with caution.

**Table 4.4**: Parameter Bias across Conditions

| Simulation Conditions | | | | Relative Parameter Bias | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Sample model | $N$ | $Mspe(Y_{imt})$ | Method Corr | $a_1$ | $a_2$ | $a_3$ | $b$ | $c'$ | *Index MM* | *IE* |
| M4 | 200 | 0.16 | 0.2 | 0.02 | -0.01 | 0.00 | 0.01 | -0.03 | 0.00 | 0.04 |
| M4 | 200 | 0.40 | 0.2 | 0.02 | -0.01 | 0.00 | 0.01 | -0.03 | -0.01 | 0.04 |
| M4 | 200 | 0.64 | 0.2 | 0.02 | -0.01 | 0.00 | 0.01 | -0.03 | -0.01 | 0.04 |
| M4 | 200 | 0.16 | 0.5 | 0.02 | -0.01 | 0.00 | 0.01 | -0.03 | 0.00 | 0.04 |
| M4 | 200 | 0.40 | 0.5 | 0.02 | -0.01 | 0.00 | 0.01 | -0.03 | -0.01 | 0.04 |
| M4 | 200 | 0.64 | 0.5 | 0.02 | -0.01 | 0.00 | 0.01 | -0.03 | -0.01 | 0.04 |
| M4 | 400 | 0.16 | 0.2 | 0.01 | 0.00 | 0.00 | 0.02 | -0.02 | 0.00 | 0.04 |
| M4 | 400 | 0.40 | 0.2 | 0.01 | 0.00 | 0.00 | 0.02 | -0.02 | 0.00 | 0.03 |
| M4 | 400 | 0.64 | 0.2 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 |
| M4 | 400 | 0.16 | 0.5 | 0.01 | 0.00 | 0.00 | 0.02 | -0.02 | 0.00 | 0.04 |
| M4 | 400 | 0.40 | 0.5 | 0.01 | 0.00 | 0.00 | 0.02 | -0.02 | 0.00 | 0.03 |
| M4 | 400 | 0.64 | 0.5 | 0.01 | 0.00 | 0.00 | 0.02 | -0.02 | 0.00 | 0.03 |
| M4 | 850 | 0.16 | 0.2 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 |
| M4 | 850 | 0.40 | 0.2 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 |
| M4 | 850 | 0.64 | 0.2 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 |
| M4 | 850 | 0.16 | 0.5 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 |
| M4 | 850 | 0.40 | 0.5 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 |
| M4 | 850 | 0.64 | 0.5 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 |
| LVMM | 200 | 0.16 | 0.2 | **0.17** | 0.02 | -0.09 | 0.03 | **0.19** | -0.07 | **0.22** |
| LVMM | 200 | 0.40 | 0.2 | **0.24** | 0.02 | **-0.19** | 0.03 | **0.30** | **-0.18** | **0.28** |
| LVMM | 200 | 0.64 | 0.2 | **0.12** | 0.01 | -0.04 | 0.03 | 0.09 | -0.02 | **0.17** |
| LVMM | 200 | 0.16 | 0.5 | **0.21** | 0.04 | **-0.11** | 0.07 | **0.24** | -0.05 | **0.30** |
| LVMM | 200 | 0.40 | 0.5 | **0.39** | 0.09 | **-0.32** | **0.13** | **0.53** | **-0.23** | **0.58** |
| LVMM | 200 | 0.64 | 0.5 | **0.15** | 0.01 | -0.06 | 0.06 | **0.12** | -0.02 | **0.22** |
| LVMM | 400 | 0.16 | 0.2 | **0.17** | 0.03 | -0.08 | 0.03 | **0.19** | -0.06 | **0.22** |
| LVMM | 400 | 0.40 | 0.2 | **0.24** | 0.02 | **-0.20** | 0.02 | **0.32** | **-0.19** | **0.28** |
| LVMM | 400 | 0.64 | 0.2 | **0.12** | 0.01 | -0.03 | 0.03 | **0.12** | -0.01 | **0.17** |
| LVMM | 400 | 0.16 | 0.5 | **0.20** | 0.05 | -0.10 | 0.07 | **0.24** | -0.05 | **0.30** |
| LVMM | 400 | 0.40 | 0.5 | **0.40** | 0.10 | **-0.33** | **0.13** | **0.58** | **-0.25** | **0.60** |
| LVMM | 400 | 0.64 | 0.5 | **0.13** | 0.03 | -0.04 | 0.06 | **0.11** | 0.00 | **0.21** |
| LVMM | 850 | 0.16 | 0.2 | **0.18** | 0.01 | -0.09 | 0.02 | **0.21** | -0.09 | **0.21** |
| LVMM | 850 | 0.40 | 0.2 | **0.25** | 0.01 | **-0.21** | 0.01 | **0.34** | **-0.21** | **0.28** |
| LVMM | 850 | 0.64 | 0.2 | **0.12** | 0.01 | -0.03 | 0.03 | **0.12** | -0.01 | **0.17** |
| LVMM | 850 | 0.16 | 0.5 | **0.21** | 0.04 | **-0.10** | 0.06 | **0.26** | -0.06 | **0.30** |
| LVMM | 850 | 0.40 | 0.5 | **0.42** | 0.09 | **-0.35** | **0.12** | **0.63** | **-0.28** | **0.61** |
| LVMM | 850 | 0.64 | 0.5 | **0.14** | 0.02 | -0.04 | 0.05 | **0.13** | -0.01 | **0.20** |

*Note*. Conditions with relative parameter bias are presented in boldface.

**Table 4.5**: Standard Error Bias across Conditions

| Simulation Conditions | | | | Standard Error Bias | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Sample model | *N* | $Mspe(Y_{imt})$ | Method Corr | $a_1$ | $a_2$ | $a_3$ | $b$ | $c'$ | *Index MM* | *IE* |
| M4 | 200 | 0.16 | 0.2 | -0.04 | -0.02 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 |
| M4 | 200 | 0.40 | 0.2 | -0.04 | -0.02 | -0.01 | 0.00 | 0.00 | 0.02 | -0.01 |
| M4 | 200 | 0.64 | 0.2 | -0.05 | -0.02 | -0.01 | 0.00 | 0.00 | 0.02 | -0.01 |
| M4 | 200 | 0.16 | 0.5 | -0.04 | -0.02 | -0.01 | 0.00 | 0.00 | 0.02 | -0.01 |
| M4 | 200 | 0.40 | 0.5 | -0.04 | -0.02 | -0.01 | 0.00 | 0.00 | 0.02 | -0.01 |
| M4 | 200 | 0.64 | 0.5 | -0.05 | -0.01 | -0.01 | 0.00 | 0.00 | 0.02 | -0.01 |
| M4 | 400 | 0.16 | 0.2 | -0.01 | -0.02 | 0.02 | -0.04 | **-0.06** | 0.04 | -0.04 |
| M4 | 400 | 0.40 | 0.2 | -0.01 | -0.02 | 0.02 | -0.05 | **-0.07** | 0.03 | -0.04 |
| M4 | 400 | 0.64 | 0.2 | -0.02 | 0.02 | 0.00 | 0.04 | -0.02 | 0.00 | -0.01 |
| M4 | 400 | 0.16 | 0.5 | -0.01 | -0.02 | 0.02 | -0.04 | **-0.07** | 0.03 | -0.04 |
| M4 | 400 | 0.40 | 0.5 | -0.01 | -0.02 | 0.01 | -0.05 | **-0.07** | 0.02 | -0.04 |
| M4 | 400 | 0.64 | 0.5 | -0.02 | -0.02 | 0.01 | **-0.05** | **-0.07** | 0.02 | -0.04 |
| M4 | 850 | 0.16 | 0.2 | -0.02 | 0.01 | -0.01 | 0.04 | -0.02 | 0.00 | -0.01 |
| M4 | 850 | 0.40 | 0.2 | -0.02 | 0.02 | 0.00 | 0.04 | -0.02 | 0.00 | -0.01 |
| M4 | 850 | 0.64 | 0.2 | -0.02 | 0.02 | 0.00 | 0.04 | -0.02 | 0.00 | -0.01 |
| M4 | 850 | 0.16 | 0.5 | -0.02 | 0.01 | -0.01 | 0.04 | -0.02 | -0.01 | -0.01 |
| M4 | 850 | 0.40 | 0.5 | -0.02 | 0.02 | -0.01 | 0.04 | -0.02 | -0.01 | -0.01 |
| M4 | 850 | 0.64 | 0.5 | -0.02 | 0.02 | 0.00 | 0.04 | -0.02 | 0.00 | -0.01 |
| LVMM | 200 | 0.16 | 0.2 | **-0.07** | **-0.07** | -0.01 | -0.03 | 0.00 | 0.01 | -0.04 |
| LVMM | 200 | 0.40 | 0.2 | **-0.09** | -0.02 | -0.04 | -0.03 | -0.02 | -0.03 | -0.03 |
| LVMM | 200 | 0.64 | 0.2 | **-0.15** | -0.03 | -0.03 | -0.02 | -0.03 | 0.00 | **-0.06** |
| LVMM | 200 | 0.16 | 0.5 | **-0.07** | **-0.07** | -0.03 | -0.04 | -0.01 | 0.01 | -0.04 |
| LVMM | 200 | 0.40 | 0.5 | **-0.14** | **-0.08** | **-0.07** | **-0.08** | **-0.12** | **-0.08** | **-0.07** |
| LVMM | 200 | 0.64 | 0.5 | **-0.09** | **-0.05** | -0.03 | **-0.06** | -0.03 | -0.01 | -0.03 |
| LVMM | 400 | 0.16 | 0.2 | -0.01 | -0.01 | 0.03 | **-0.06** | **-0.07** | 0.01 | **-0.05** |
| LVMM | 400 | 0.40 | 0.2 | -0.03 | **-0.14** | **-0.05** | **-0.07** | **-0.11** | **-0.07** | **-0.06** |
| LVMM | 400 | 0.64 | 0.2 | -0.02 | 0.01 | 0.00 | 0.04 | -0.03 | -0.02 | -0.01 |
| LVMM | 400 | 0.16 | 0.5 | -0.02 | -0.01 | 0.03 | **-0.06** | **-0.08** | 0.01 | -0.05 |
| LVMM | 400 | 0.40 | 0.5 | **-0.09** | **-0.06** | 0.00 | **-0.10** | **-0.19** | -0.05 | **-0.08** |
| LVMM | 400 | 0.64 | 0.5 | -0.04 | -0.04 | 0.01 | **-0.06** | **-0.07** | 0.01 | **-0.05** |
| LVMM | 850 | 0.16 | 0.2 | 0.02 | **-0.25** | **-0.16** | 0.03 | -0.03 | **-0.14** | 0.02 |
| LVMM | 850 | 0.40 | 0.2 | 0.01 | -0.01 | **-0.06** | 0.01 | **-0.08** | **-0.07** | 0.03 |
| LVMM | 850 | 0.64 | 0.2 | -0.02 | 0.01 | 0.00 | 0.04 | -0.03 | -0.02 | -0.01 |
| LVMM | 850 | 0.16 | 0.5 | 0.01 | 0.01 | -0.02 | 0.04 | -0.03 | -0.02 | 0.03 |
| LVMM | 850 | 0.40 | 0.5 | -0.01 | **-0.07** | **-0.07** | -0.01 | **-0.12** | **-0.06** | 0.04 |
| LVMM | 850 | 0.64 | 0.5 | -0.03 | 0.00 | -0.02 | **-0.24** | **-0.12** | **-0.06** | **-0.18** |

*Note*. Conditions with relative standard error bias are presented in boldface.

**Power.** Results showing power estimates for each condition are presented in Table 4.6. All conditions with a sample size of 200 were underpowered in detecting Index MM, the indirect effect, significance of the $a_3$ path, and significance of the $c'$ paths. These four parameters had the smallest effect sizes in the study, likely influencing their lack of power in the small sample size condition. The M4 model had sufficient power to detect any of the above effects when sample size was 400 or greater. The LVMM model still showed lower than adequate power to detect the $a_3$ and Index MM pathways when sample size was 400 and method-specificity was .40.

**Coverage.** Parameter coverage was defined as the proportion of replications where the 95% confidence interval included the true population parameter value. 95% parameter coverage was very good for the M4 model. Only one condition resulted in lower than satisfactory parameter coverage for a single parameter (see Table 4.7). A sample size of $N = 200$ resulted in lower than satisfactory parameter coverage (.90 to .91) for Index MM. No other conditions in the M4 model had unsatisfactory parameter coverage. However, parameter coverage was not good for the LVMM model, with at least one parameter falling outside of the ideal coverage range across all conditions. Parameter coverage was worse in the LVMM sample models when method-specificity was equal to .40. Coverage was the worst in the LVMM models when method-specificity was equal to .40 and when the correlation among method factors was equal to .50. Results indicate that the proportion of replications containing the true parameter value was lower under these specific conditions.

**Table 4.6**: Statistical Power across Conditions

| Simulation Conditions | | | | Statistical Power | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Sample model | *N* | $Mspe(Y_{imt})$ | *Method Corr* | $a_1$ | $a_2$ | $a_3$ | $b$ | $c'$ | *Index MM* | *IE* |
| M4 | 200 | 0.16 | 0.2 | 0.90 | 0.86 | **0.63** | 0.85 | **0.65** | **0.34** | **0.64** |
| M4 | 200 | 0.40 | 0.2 | 0.90 | 0.85 | **0.62** | 0.85 | **0.65** | **0.33** | **0.63** |
| M4 | 200 | 0.64 | 0.2 | 0.90 | 0.86 | **0.62** | 0.85 | **0.65** | **0.32** | **0.63** |
| M4 | 200 | 0.16 | 0.5 | 0.90 | 0.85 | **0.63** | 0.85 | **0.65** | **0.35** | **0.63** |
| M4 | 200 | 0.40 | 0.5 | 0.90 | 0.85 | **0.61** | 0.85 | **0.65** | **0.34** | **0.64** |
| M4 | 200 | 0.64 | 0.5 | 0.90 | 0.85 | **0.61** | 0.85 | **0.65** | **0.32** | **0.63** |
| M4 | 400 | 0.16 | 0.2 | 1.00 | 0.99 | 0.93 | 0.99 | 0.90 | 0.85 | 0.97 |
| M4 | 400 | 0.40 | 0.2 | 1.00 | 0.99 | 0.93 | 0.98 | 0.90 | 0.85 | 0.97 |
| M4 | 400 | 0.64 | 0.2 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| M4 | 400 | 0.16 | 0.5 | 1.00 | 0.99 | 0.93 | 0.98 | 0.90 | 0.85 | 0.97 |
| M4 | 400 | 0.40 | 0.5 | 1.00 | 0.99 | 0.93 | 0.98 | 0.90 | 0.85 | 0.97 |
| M4 | 400 | 0.64 | 0.5 | 1.00 | 0.99 | 0.92 | 0.98 | 0.91 | 0.84 | 0.97 |
| M4 | 850 | 0.16 | 0.2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 | 1.00 |
| M4 | 850 | 0.40 | 0.2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 | 1.00 |
| M4 | 850 | 0.64 | 0.2 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| M4 | 850 | 0.16 | 0.5 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| M4 | 850 | 0.40 | 0.5 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| M4 | 850 | 0.64 | 0.5 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| LVMM | 200 | 0.16 | 0.2 | 0.96 | 0.90 | **0.59** | 0.86 | 0.84 | **0.32** | **0.76** |
| LVMM | 200 | 0.40 | 0.2 | 0.98 | 0.90 | **0.45** | 0.86 | 0.87 | **0.23** | **0.75** |
| LVMM | 200 | 0.64 | 0.2 | 0.94 | 0.86 | **0.59** | 0.84 | **0.75** | **0.30** | **0.69** |
| LVMM | 200 | 0.16 | 0.5 | 0.97 | 0.92 | **0.59** | 0.87 | 0.86 | **0.33** | **0.79** |
| LVMM | 200 | 0.40 | 0.5 | 0.98 | 0.92 | **0.39** | 0.87 | 0.92 | **0.22** | 0.82 |
| LVMM | 200 | 0.64 | 0.5 | 0.94 | 0.86 | **0.58** | 0.84 | **0.76** | **0.30** | **0.70** |
| LVMM | 400 | 0.16 | 0.2 | 1.00 | 1.00 | 0.90 | 0.99 | 0.98 | 0.82 | 0.98 |
| LVMM | 400 | 0.40 | 0.2 | 1.00 | 0.99 | **0.76** | 0.98 | 0.99 | **0.63** | 0.98 |
| LVMM | 400 | 0.64 | 0.2 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| LVMM | 400 | 0.16 | 0.5 | 1.00 | 1.00 | 0.89 | 0.99 | 0.99 | 0.83 | 0.99 |
| LVMM | 400 | 0.40 | 0.5 | 1.00 | 1.00 | **0.67** | 0.99 | 0.99 | **0.58** | 0.99 |
| LVMM | 400 | 0.64 | 0.5 | 1.00 | 0.99 | 0.90 | 0.99 | 0.95 | 0.81 | 0.98 |
| LVMM | 850 | 0.16 | 0.2 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| LVMM | 850 | 0.40 | 0.2 | 1.00 | 1.00 | 0.97 | 1.00 | 1.00 | 0.97 | 1.00 |
| LVMM | 850 | 0.64 | 0.2 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| LVMM | 850 | 0.16 | 0.5 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |
| LVMM | 850 | 0.40 | 0.5 | 1.00 | 1.00 | 0.93 | 1.00 | 1.00 | 0.90 | 1.00 |
| LVMM | 850 | 0.64 | 0.5 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 |

*Note*. Conditions with low power are presented in boldface.

**Table 4.7**: Parameter Coverage across Conditions

| Simulation Conditions | | | | Parameter Coverage | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Sample model | $N$ | $Mspe(Y_{imt})$ | Method Correlation | $a_1$ | $a_2$ | $a_3$ | $b$ | $c'$ | *Index MM* | *IE* |
| M4 | 200 | 0.16 | 0.2 | 0.94 | 0.94 | 0.95 | 0.95 | 0.94 | 0.91 | 0.93 |
| M4 | 200 | 0.40 | 0.2 | 0.94 | 0.94 | 0.95 | 0.95 | 0.94 | **0.91** | 0.93 |
| M4 | 200 | 0.64 | 0.2 | 0.94 | 0.94 | 0.95 | 0.95 | 0.94 | **0.90** | 0.93 |
| M4 | 200 | 0.16 | 0.5 | 0.94 | 0.94 | 0.95 | 0.95 | 0.94 | 0.91 | 0.93 |
| M4 | 200 | 0.40 | 0.5 | 0.94 | 0.94 | 0.95 | 0.95 | 0.93 | **0.90** | 0.93 |
| M4 | 200 | 0.64 | 0.5 | 0.94 | 0.94 | 0.94 | 0.95 | 0.93 | **0.91** | 0.93 |
| M4 | 400 | 0.16 | 0.2 | 0.94 | 0.95 | 0.95 | 0.95 | 0.93 | 0.94 | 0.94 |
| M4 | 400 | 0.40 | 0.2 | 0.94 | 0.95 | 0.94 | 0.95 | 0.93 | 0.94 | 0.94 |
| M4 | 400 | 0.64 | 0.2 | 0.94 | 0.95 | 0.95 | 0.96 | 0.95 | 0.94 | 0.94 |
| M4 | 400 | 0.16 | 0.5 | 0.94 | 0.95 | 0.95 | 0.95 | 0.93 | 0.94 | 0.94 |
| M4 | 400 | 0.40 | 0.5 | 0.94 | 0.95 | 0.95 | 0.95 | 0.93 | 0.94 | 0.93 |
| M4 | 400 | 0.64 | 0.5 | 0.94 | 0.95 | 0.94 | 0.95 | 0.93 | 0.93 | 0.93 |
| M4 | 850 | 0.16 | 0.2 | 0.94 | 0.95 | 0.95 | 0.96 | 0.95 | 0.94 | 0.94 |
| M4 | 850 | 0.40 | 0.2 | 0.94 | 0.95 | 0.95 | 0.96 | 0.95 | 0.93 | 0.94 |
| M4 | 850 | 0.64 | 0.2 | 0.94 | 0.95 | 0.95 | 0.96 | 0.95 | 0.94 | 0.94 |
| M4 | 850 | 0.16 | 0.5 | 0.94 | 0.96 | 0.95 | 0.96 | 0.95 | 0.93 | 0.94 |
| M4 | 850 | 0.40 | 0.5 | 0.94 | 0.95 | 0.94 | 0.96 | 0.95 | 0.93 | 0.94 |
| M4 | 850 | 0.64 | 0.5 | 0.94 | 0.95 | 0.94 | 0.96 | 0.95 | 0.93 | 0.94 |
| LVMM | 200 | 0.16 | 0.2 | **0.88** | 0.94 | 0.94 | 0.93 | 0.91 | **0.89** | 0.95 |
| LVMM | 200 | 0.40 | 0.2 | **0.82** | 0.94 | 0.91 | 0.93 | **0.87** | **0.85** | 0.95 |
| LVMM | 200 | 0.64 | 0.2 | **0.90** | 0.95 | 0.95 | 0.94 | 0.92 | **0.90** | 0.94 |
| LVMM | 200 | 0.16 | 0.5 | **0.85** | 0.94 | 0.94 | 0.93 | **0.90** | **0.90** | 0.96 |
| LVMM | 200 | 0.40 | 0.5 | **0.66** | **0.90** | **0.84** | **0.90** | **0.70** | **0.81** | **0.87** |
| LVMM | 200 | 0.64 | 0.5 | **0.89** | 0.95 | 0.95 | 0.92 | 0.91 | **0.90** | 0.95 |
| LVMM | 400 | 0.16 | 0.2 | **0.86** | 0.95 | 0.95 | 0.93 | **0.87** | **0.91** | 0.92 |
| LVMM | 400 | 0.40 | 0.2 | **0.74** | 0.94 | **0.90** | 0.94 | **0.77** | **0.85** | 0.91 |
| LVMM | 400 | 0.64 | 0.2 | **0.87** | 0.95 | 0.95 | 0.95 | **0.90** | 0.93 | 0.92 |
| LVMM | 400 | 0.16 | 0.5 | **0.80** | 0.94 | 0.94 | 0.93 | **0.83** | 0.92 | **0.91** |
| LVMM | 400 | 0.40 | 0.5 | **0.46** | **0.89** | **0.76** | **0.88** | **0.50** | **0.81** | **0.74** |
| LVMM | 400 | 0.64 | 0.5 | **0.88** | 0.94 | 0.94 | 0.91 | 0.91 | 0.92 | 0.94 |
| LVMM | 850 | 0.16 | 0.2 | **0.72** | 0.95 | 0.93 | 0.96 | **0.79** | **0.90** | **0.89** |
| LVMM | 850 | 0.40 | 0.2 | **0.53** | 0.94 | **0.80** | 0.96 | **0.57** | **0.81** | **0.85** |
| LVMM | 850 | 0.64 | 0.2 | **0.87** | 0.95 | 0.95 | 0.95 | **0.90** | 0.93 | 0.92 |
| LVMM | 850 | 0.16 | 0.5 | **0.63** | 0.94 | 0.92 | 0.94 | **0.73** | 0.92 | **0.81** |
| LVMM | 850 | 0.40 | 0.5 | **0.14** | **0.88** | **0.56** | **0.88** | **0.19** | **0.70** | **0.42** |
| LVMM | 850 | 0.64 | 0.5 | **0.83** | 0.95 | 0.95 | 0.95 | **0.88** | 0.94 | 0.91 |

*Note*. Conditions with unacceptable parameter coverage are presented in boldface.

**Discussion and Conclusions**

This study was the first simulation study to examine moderated mediation in a multimethod framework. Overall, the M4 model performed well in the simulated conditions, especially compared to the LVMM. The M4 model did not have convergence issues, likely due to the manner in which trait and method factors were constructively defined in the CT-C($M$ – 1) approach. When fitting a sample M4 model to data generated from a population M4 model, a sample size of 850 had adequate power, adequate parameter coverage, unbiased parameter estimates, and unbiased standard errors across all moderated and mediated effects. A sample size of 400 contained satisfactory power, but had some issues with standard error bias for the $c'$ parameter estimate. Sample sizes of 200 lacked the power necessary to detect moderated mediation effects and had issues with parameter coverage, but did not show parameter bias nor standard error bias.

A different story emerged when fitting the sample LVMM to data generated from a population M4 model. The LVMM model performed poorly across most conditions, presumably because the population model contained variance due to a method factor that was excluded in the LVMM sample model. One particularly interesting finding was that equal amounts of method-specificity and trait consistency (i.e., the condition where $Mspe(Y_{imt}) = .40$) resulted in greater parameter bias across more parameters and had worse parameter coverage across more parameters. More specifically, conditions with equal amounts of method and trait variance had a strong effect on parameter bias, upward biasing estimates of the $a_1$, $c'$, and the indirect effect, but downward biasing the moderated effects. Such suggests that not appropriately modeling method-specific variance can lead to an underestimation of the moderated effect and overestimation of the direct and indirect effects.

Additional examination of other model parameters showed that method-specificity was being treated as random measurement error when models were misspecified. Under conditions with high method-specificity, model misspecification affected error variance estimates specific to the non-reference variables. Method effects were modeled as measurement error, which led to less (but still unacceptable) bias in the moderated mediation effects. Under conditions with equal method-specificity and trait consistency, LVMM models showed slightly inflated error variances for both reference and non-reference method variables, overestimated factor loadings for non-reference methods, and underestimated factor loadings for reference methods. Method effects were modeled as both error **and trait** variance, resulting in unacceptable, larger bias in the moderated mediation effects. Under conditions with low method-specificity, LVMM models showed similar results to the condition with equal method-specificity and trait consistency but to a lesser extent. Overall, when method effects were not appropriately captured by a method factor, bias ensued. It is therefore imperative that method effects be appropriately modeled to avoid bias in the moderated mediation pathways.

Power was adequate across conditions with sample sizes of at least 400. One related study (Cheung & Lau, 2017) examined power in a general LVMM as compared to regression moderated mediation model. Their study was more comprehensive in that they examined more effect size estimates for different pathways of interest. They found adequate power to detect a moderate moderated effect (.4) with as few as 100 individuals, yet when the moderated effect decreased in magnitude (.2), power to detect the moderated effect decreased to .38. Cheung and Lau additionally examined power to detect a small interaction effect ( $a_3$ = .20) in a sample size of 200, finding that power was rather low at .68. The present study examined a similarly sized interaction effect ( $a_3$ = .15) in a sample size of 200. Like Cheung and Lau, the present study revealed that $N$ = 200 resulted in a lack of power to detect the small moderated effect, power = .61 to .63. Although the present study showed there was not enough power to detect effects, it also showed that estimates of the underpowered effect were unbiased. These two results support the notion that sample sizes of 200 are not adequate for examining moderated mediation when the interaction effect is small. Since this small interaction effect was the average effect found in current literature within the meta-analytic review, using a sample size of 200 is not recommended with the M4 approach.

**Strengths of the Monte Carlo simulation study.** This was the first study to evaluate the applicability of the M4 model across simulated conditions. Although few simulation conditions were examined, population values for the most relevant parameters were 1) based on effect sizes commonly found in moderated mediation studies and are thus relevant to current applied research on moderated mediation analysis, or 2) based on the application of the M4 model as presented in Chapter IV. Only levels of method-specificity were chosen for theoretical reasons.

The meta-analytic review offered valuable insight into how researchers are currently conceptualizing and applying moderated mediation models. Most articles are using multiple variables in a single path model, thus potentially complicating moderated mediation results and making analyses such a first-stage moderated mediation less relevant than more complex structural path models. Future research should examine how best to model these complex relationships among variables while still appropriately accounting for the measurement structure of variables. The literature review also showed the average moderated mediation effects that have been found in developmental psychology, clinical psychology, and prevention science research.

**Limitations and future research.** One finding from the literature review that was not discussed much in the results was that nine (of an original 39) studies were dropped from the review because of the way that they reported moderated mediation results. Effects such as the indirect effect and the conditional indirect effects were often reported in articles, but specific effects, such as the $a_1$ path, were frequently omitted from reports. Indirect and conditional indirect effects are important and can be more meaningfully interpreted than some of the specific effects. However, effects aggregated from more than one pathway could not be standardized meaningfully in a meta-analytic framework. Guidelines for reporting results from moderated mediation analysis are beginning to emerge, in part due to the work of Hayes (2013). Future research is needed about reporting moderated mediation analysis appropriate for meta-analyzing results.

The Monte Carlo simulation in the present study included few conditions, which was a limitation for generalizing results across different data conditions. Perhaps the M4 model only works under these very specific conditions. Future research should examine the M4 model under additional conditions, for example different levels of missingness, different values of method-specificity and reliability, larger and smaller effects between constructs, and skewed or kurtotic data distributions.

Relatedly, this first presentation of the M4 model used a first-stage moderated mediation model. Other moderated mediation models exist (Hayes, 2013; Edwards & Lambert, 2007). Future research could examine second-stage M4 models, direct effect M4 models, various combinations of different moderated mediation effects in M4 models. Further, future research could examine the influence of adding more moderators or mediators into the model.

Another limitation of the Monte Carlo simulation study was that only two methods and three indicators per trait-method unit were used in the M4 modeling approach. Additional indicators and methods could impact the performance of the M4 model, and could be examined in future research. Further, indicators were partially invariant across methods and traits, which is unlikely to occur in applied contexts. Invariance was constrained to more directly calculate the consistency and method-specificity estimates. Future research should examine the model under conditions which do not assume measurement invariance across methods.

The simulation study did not examine the use of bias-corrected bootstrap methods due to the time that it would have taken for each model to run. With the emergence of very high-powered computing systems as well as innovative algorithms, one future line of research could examine an estimation approach that adequately accounts for the nonnormal distribution of the indirect effect using less computationally intensive methods. Although one such method exists (the distribution of the product of coefficients approach; MacKinnon et al., 2002; MacKinnon et al., 2004), it did not work with the present study due to the inclusion of more than a single predictor (both $X$ and $W$) as well as the latent interaction term, $XW$. Future research could examine correction approaches that require less computational time and account for a wide variety of mediation or moderated mediation models.

Finally, the LMS approach, while useful for evaluating moderation, was rather computationally intensive, especially when combined with the Monte Carlo simulation design. Future research could examine other approaches to estimating latent variable interaction effects using less computationally intensive methods that work similarly or better than the LMS approach. Cheung and Lau (2017) suggested the two-stage least squares (2SLS) approach (Bollen, 1996) as an alternative to LMS. 2SLS has shown relatively unbiased latent interaction effects, similar to the LMS approach, and may be a practical approach to calculating latent interaction terms.

**Conclusions.** To conclude, the M4 model is a viable model that was used to estimate moderated mediation estimates using a multimethod framework. When method effects were present in data, this model appropriately handled them and provided unbiased estimates across various conditions. Each research question was directly addressed to end this chapter.

*Under which and how many simulated conditions did the M4 model have adequate power to detect the mediated and moderated effects?* The M4 model was adequately powered to detect all moderated and mediated effects in 12 of 18 conditions. The model had adequate power as long as $N = 400$ or 850.

*Under which and how many simulated conditions did the M4 model produce biased estimates or standard errors of the mediated or moderated effects?* When the M4 model was used to evaluate moderated mediation effects, parameter bias was negligible; 0 of 18 conditions produced biased estimates. Further, standard errors of the $c'$ parameter (and one instance of bias for the *b* parameter) were biased when sample size was 400. Standard errors were unbiased in the remaining 13 out of 18 conditions.

*Under which and how many simulated conditions did a misspecified model without method factors (i.e., the M4 model without method factors, equivalent to a latent variable moderated mediation model [LVMM]; Cheung & Lau, 2017) have adequate power to detect the mediated and moderated effects?* The LVMM model showed worse power than the M4 model. Similar to the M4 model, the LVMM model lacked power to detect significant effects with a sample size of $N = 200$. However, the LVMM model also lacked power to detect significant effects when $N = 400$ and method-specificity was equal to 0.5. The model had adequate power across estimates in the remaining 10 out of 18 conditions.

*Under which and how many simulated conditions did the M4 model without method factors produce biased parameter estimates or standard errors of the mediated or moderated effects?* The LVMM model contained biased parameter estimates for at least one parameter estimate across every condition, so 18 of 18 conditions produced biased estimates. The LVMM model further contained ample standard error bias across most conditions. Fifteen out of 18 conditions contained standard error bias.

*Which conditions produced higher instances of non-converged solutions?* Although convergence rates were very high across all conditions, the conditions where data was fit to the LVMM model had slightly lower convergence rates than conditions where data was fit to the M4 model.

*Which conditions produced low parameter coverage for the moderated mediation population parameters?* Low parameter coverage was more pronounced in the LVMM model than in the M4 model. This was expected since the LVMM model was misspecified. Further, parameter coverage was lower in the LVMM conditions when method-specificity was moderate and method correlations were large.

# CHAPTER VI

# SUMMARY AND CONCLUSIONS

The objective of the present research was to create a multimethod moderated mediation (M4) model to more appropriately model data that contained a multimethod data structure. This model was applied to a dataset of child developmental behaviors and was also examined using a Monte Carlo simulation study.

The M4 model was the first known model to address appropriate ways to model multimethod data in moderated mediation analysis. Although multimethod designs have been advanced in psychological and other social sciences (Achenbach, 2006; Cole, 1987; De Los Reyes & Kazdin, 2005; Hopwood & Bornstein, 2014; Meyer et al., 2001; Morris et al., 2006), few approaches have implemented quantitative multimethod designs such as the CT-C($M$ – 1) model in combination with approaches used to examine relationships among variables such as moderated mediation. This is potentially problematic since the present research found that excluding the measurement structure from the analysis model led to biased results. When data were truly multimethod (i.e., true variance from observed variables was attributed to both trait and method factors), excluding a multimethod measurement structure in the analysis of data resulted in parameter and standard error bias. When the model was misspecified, the simulation study showed that mediated effects were overestimated while the moderated effects were underestimated. Specifically, mediated parameter estimates were *overestimated* by anywhere from 12% to 40% for $a_1$, 1% to 13% for $b$, and 17% to 60% for the indirect effect. In contrast, the moderated parameter estimates were *underestimated* by anywhere from 3% to 33% for $a_3$, and 0% to 25% for the Index MM. Thus, moderating effects were more difficult to detect while the mediated effects were overestimated if the multimethod measurement structure of the variables was not properly modeled. In order to avoid bias, one recommendation is to use methods such as the M4 model to appropriately model the measurement structure of multimethod data as well as the structural relationships among variables.

Although framed in a multimethod framework, the simulation study examined the presence of some non-trait factor (i.e., method factor) that impacted the variance of the observed variables. Such a situation may be informative for other measurement situations. For example, variance from the method factor could potentially represent variance from any systematic effect, including a confounding variable, situational fluctuations to behavior, or an environmental factor that was left out of analysis. The interpretation I have applied to this variance was method effects, but other systematic sources of variance could result in the same general findings.

Measurement does impact results, and the measurement structure should be modeled when evaluating structural relationships among variables. One study evaluating the impact of incorrectly modeling the bifactor measurement structure in mediation analysis (Gonzalez & MacKinnon, 2018) emphasized the necessity of correctly modeling the measurement structure of variables. In their study, not appropriately modeling the measurement structure also resulted in biased and underpowered findings. It seems that excluding the appropriate measurement structure from analysis has the potential to impact study results across a wide range of measurement practices as well as different statistical analyses. Additionally, Gonzalez and MacKinnon (2018) note that measurement issues are relatively understudied in statistical mediation analysis. I would agree. Researchers typically do not study measurement issues within mediation nor moderated mediation analysis with few exceptions (e.g., Fritz et al., 2016; Gonzalez & MacKinnon, 2018; Hoyle & Kenny, 1999; Papa et al., 2015).

When the measurement structure was ignored in the present study (i.e., the method factor was not modeled), results for all parameters resulted in some form of bias across all conditions. The issue of measurement in moderated mediation analysis is not simply about using complex measurement models to evaluate data; it is about accurately modeling data to avoid biased results.

**Implications**

The present study has important implications for applied as well as quantitative research. First and foremost, the M4 model did not have enough power to detect moderated nor mediated effects when the sample size was 200. This model should not be used (but is still preferable to a latent variable moderated mediation model) when the sample size is less than 400. Importantly, estimates and standard errors when the sample size was 200 were not biased, so although the model may not have shown adequate power, estimates were unlikely to be biased given the limited conditions of the simulation study. Applied researchers are urged to use the M4 model when they have data from multiple methods with a sample size of at least 400.

Although the model did not have the power to detect effects at lower sample sizes it may be possible to examine the M4 model in a Bayesian framework. Bayesian approaches have been shown more ideal for smaller sample sizes in mediation analysis (Yuan & MacKinnon, 2009). Perhaps the same is true of moderated mediation analysis. Because the effects from the simulation study were not biased, Bayesian M4 models are a potential avenue for both applied as well as quantitative research with smaller sample sizes.

One important implication for both quantitative as well as applied research is the circumstances required to evaluate the M4 model as presented in this paper. As it currently stands, the M4 model has only been evaluated examining one moderator and mediator in first-stage moderated mediation using continuous variables measured by structurally different methods. Further, only one method for evaluating the latent interaction term and one approach to evaluating the conditional indirect effect were examined. These limited conditions do not represent all potential avenues for the M4 model. Various M4 models could be created to evaluate interchangeable methods of measurement, multiple mediators or moderators, second-stage moderated mediation, etc. The present approach did not consider these alternative models due to the complexity that would be required, which was beyond the scope of the project. Not only is this additional research needed to examine multimethod moderated mediation, but these extensions are also needed in the context of the simpler latent variable moderated mediation.

**Extensions of the M4 model**

The M4 model, while appropriate for single-level, continuous, multimethod data, is not an umbrella analysis that should be used for all research designs when researchers wish to examine multimethod data using moderated mediation analysis. In fact, I would discourage applied researchers from moving too far away from the presented approach, mostly because of the complex modeling nature of the M4 approach. Acknowledging that the M4 model is limited in its capabilities is important for both the utility and advancement of the approach. There are many data structures that the M4 model was not specifically designed to handle, including complex data and categorical variables.

Currently, there are approaches to evaluate moderated mediation using multilevel designs (e.g., Bauer, Preacher, & Gil, 2006) and there are also approaches to evaluate multitrait multimethod analysis using multilevel designs (Maas et al., 2009). There is a potential to combine these approaches to examine multimethod moderated mediation analysis using a multilevel framework. Doing so would result in a model that is accessible to researchers from different fields who are trained in multilevel modeling but not in structural equation modeling. Further, the multilevel configuration of the model would be simpler, yet it would be inappropriate for structurally different methods and would not have the same flexibility as the current CFA approach (e.g., Eid et al., 2008; Maas et al., 2009).

Categorical approaches to moderated mediation analysis are simpler than continuous approaches, yet require using a different framework. When a categorical variable is used as the moderating variable, one can think of moderated mediation analysis as a multiple group design, with the group being the moderating variable. For example, many applications of moderated mediation analysis may use gender as a moderating factor. Gender is often dichotomized to men and women, and researchers are interested in whether processes differ between men and women. In the M4 approach, categorical moderators such as gender could be treated as the grouping variable, and separate models could be run separately for men and women. Essentially, in a categorical moderating case, researchers could run a multimethod mediation model (Papa et al., 2015) separated by group. Future research is needed to determine the power, bias, coverage, and error of such a model.

In addition to these extensions to complex and categorical data, the M4 approach was limited in its use of only *one* CFA-MTMM model. The multimethod data structure assumed in the M4 model was the CT-C($M$ – 1) structure to appropriately model data from structurally different methods (e.g., parent report compared to clinical assessment). However, this method would not be not appropriate for data that did not measure data using multiple methods. In fact, the approach is not even relevant for data gathered from interchangeable methods (e.g., peer report). Interchangeable methods require using multilevel confirmatory factor analysis models (Eid et al., 2008). The multilevel confirmatory factor analysis model is one of many models used to account for different measurement structures.

Other multimethod measurement models have been developed for nested data (Koch, Schultze, Burrus, Roberts, & Eid, 2015), Bayesian approaches (Helm, Castro-Schilo, & Oravecz, 2017), and non-independent methods where raters or sources evaluate more than one individual (Schultze, Koch, & Eid, 2015). These approaches to modeling multimethod data all address how best to model the true measurement structures of variables under different data conditions. Each of these approaches could potentially be used as the measurement structure of the M4 model or other models that examine the structural relationships among variables using multimethod data. Future research may wish to examine a more generalized approach to examining moderated mediation using multimethod designs.

The M4 model was rather limited in the number of relationships that were examined. Specifically, I only examined first-stage moderated mediation (Edwards & Lambert, 2007) as the structural portion of the model, which is appropriate when the moderator is expected to influence the *a*-pathway but no other pathway. First-stage moderated mediation is only one of seven models that can be used to examine moderated mediation with one moderator and one mediator. Including additional mediators or moderators would result in far more complex models to evaluate, yet the meta-analytic literature review showed that multiple effects were often included in the same moderated mediation model. Future research could advance the M4 model by examining more moderators, more mediators, more dependent outcomes, or more independent variables.

The M4 model, currently, is a cross-sectional model and cannot appropriately account for longitudinal effects. In mediation analysis, longitudinal effects are necessary to examine how processes develop across time (Bollen & Curran, 2006; Cole & Maxwell, 2003; Maxwell & Cole, 2007; Selig & Preacher, 2009). Future research is needed to examine longitudinal extensions of the M4 model. Specifically, it would be informative to begin by examining the cross-lagged mediation model (Cole & Maxwell, 2003) using multimethod data and adding a moderating term to the model.

**Conclusions**

In sum, the M4 model advances an approach to moderated mediation analysis appropriate for multimethod research designs. Both the application and Monte Carlo simulation studies showed that the model performed well under different conditions. The Monte Carlo simulation further reflected the necessity of using the M4 model as compared to a more general latent variable moderated mediation model when even relatively minimal method effects were present. The project adds to the emerging pool of research that examining the measurement structure of variables in mediation and moderated mediation analysis. Overall, the current project was intended to advance the quantitative knowledge of moderated mediation analysis in the presence of multimethod data.

**References**

Achenbach, T. M. (2006). As others see us: Clinical and research implications of cross-informant correlations for psychopathology. *Current Directions in Psychological Science*, *15*(2), 94-98.

Achenbach, T. M. (2011). Commentary: Definitely more than measurement error: But how should we understand and deal with informant discrepancies? *Journal of Clinical Child & Adolescent Psychology*, *40*(1), 80-86.

Achenbach, T. M., McConaughy, S. H., & Howell, C. T. (1987). Child/adolescent behavioral and emotional problems: Implications of cross-informant correlations for situational specificity. *Psychological Bulletin*, *101*(2), 213-232.

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. United States: Sage.

Baardstu, S., Karevold, E. B., & von Soest, T. (2017). Childhood antecedents of Agreeableness: A longitudinal study from preschool to late adolescence. *Journal of Research In Personality*, *67*202-214. doi:10.1016/j.jrp.2016.10.007

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly*, 421-458.

Baron, R. M, & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173-1182.

Barry, T. D., Lyman, R. D., & Klinger, L. G. (2002). Academic underachievement and attention-deficit/hyperactivity disorder: The negative impact of symptom severity on school performance. *Journal of School Psychology*, *40*(3), 259-283.

Bates, D., Mächler, M., Bolker, B., Walker, S., Christensen, R. H. B. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1-48. doi: 10.18637/jss.v067.i01

Bauer, D. J., Preacher, K. J., & Gil, K. M. (2006). Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: new procedures and recommendations. *Psychological Methods*, *11*(2), 142.

Beauchaine, T. P., Hinshaw, S. P., & Pang, K. L. (2010). Comorbidity of attention-deficit/hyperactivity disorder and early-onset conduct disorder: Biological, environmental, and developmental mechanisms. *Clinical Psychology: Science and Practice*, *17*(4), 327-336.

Bollen, K. A. (1989). *Structural equations with latent variables.* New-York: Wiley

Bollen, K. A., & Stine, R. (1990). Direct and indirect effects: Classical and bootstrap estimates of variability. *Sociological Methodology, 20*, 115-140.

Bollen, K. A. (1996). An alternative two stage least squares (2SLS) estimator for latent variable equations. *Psychometrika*, *61*(1), 109-121.

Brock, R. L., Kochanska, G., O'Hara, M. W., & Grekin, R. S. (2015). Life satisfaction moderates the effectiveness of a play-based parenting intervention in low-income mothers and toddlers. *Journal of Abnormal Child Psychology*, *43*(7), 1283-1294. doi:10.1007/s10802-015-0014-y

Bullock, J. G., Green, D. P., & Ha, S. E. (2010). Yes, but what's the mechanism? (don't expect an easy answer). *Journal of Personality and Social Psychology*, *98*(4), 550-558. doi: 10.1037/a0018933.

Bunford, N., Evans, S. W., Becker, S. P., & Langberg, J. M. (2015). Attention-deficit/hyperactivity disorder and social skills in youth: A moderated mediation model of emotion dysregulation and depression. *Journal of Abnormal Child Psychology*, *43*(2), 283-296. doi:10.1007/s10802-014-9909-2

Burns, G. L., & Lee, S. (2011). *Child and adolescent disruptive behavior inventory–Parent version 5.0.* Pullman, WA: Author.

Burns, G. L., & Walsh, J. A. (2002). The influence of ADHD–hyperactivity/impulsivity symptoms on the development of oppositional defiant disorder symptoms in a 2-year longitudinal study. *Journal of abnormal child psychology*, *30*(3), 245-256.

Burns, G. L., Boe, B., Walsh, J. A., Sommers-Flanagan, R., & Teegarden, L. A. (2001). A confirmatory factor analysis on the DSM-IV ADHD and ODD symptoms: What is the best model for the organization of these symptoms? *Journal of Abnormal Child Psychology*, *29*(4), 339-349.

Burns, G. L., de Moura, M. A., Walsh, J. A., Desmul, C., Silpakit, C., & Sommers-Flanagan, J. (2008). Invariance and convergent and discriminant validity between mothers' and fathers' ratings of oppositional defiant disorder toward adults, ADHD-HI, ADHD-IN, and academic competence factors within Brazilian, Thai, and American children. *Psychological Assessment*, *20*(2), 121-130.

Burns, G. L., de Moura, M. A., Beauchaine, T. P., & McBurnett, K. (2014). Bifactor latent structure of ADHD/ODD symptoms: predictions of dual-pathway/trait-impulsivity etiological models of ADHD. *Journal of Child Psychology and Psychiatry, 55*(4), 393-401. doi: 10.1111/jcpp.12165

Burns, G. L., Servera, M., Bernad, M., Carrillo, J. M., & Geiser, C. (2014). Ratings of ADHD symptoms and academic impairment by mothers, fathers, teachers and aides: Construct validity within and across settings as well as occasions. *Psychological Assessment, 26*, 1247-1258. doi:10.1037/pas0000008

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin, 56*(2), 81-105.

Castro-Schilo, L., Widaman, K. F., & Grimm, K. J. (2013). Neglect the structure of multitrait-multimethod data at your peril: implications for associations with external variables. *Structural Equation Modeling: A Multidisciplinary Journal*, *20*(2), 181-207.

Chardon, M. L., Janicke, D. M., Carmody, J. K., & Dumont-Driscoll, M. C. (2016). Youth internalizing symptoms, sleep-related problems, and disordered eating attitudes and behaviors: A moderated mediation analysis. *Eating Behaviors*, *21*, 99-103.

Cheung, G. W., & Lau, R. S. (2017). Accuracy of parameter estimates and confidence intervals in moderated mediation models: A comparison of regression and latent moderated structural equations. *Organizational Research Methods, 20*(4), 746-769. doi: 10.1177/1094428115595869

Cole, D. A., & Maxwell, S. E. (2003). Testing mediational models with longitudinal data: Questions and tips in the use of structural equation modeling. *Journal of Abnormal Psychology*, *112*(4), 558-577.

Cole, D. A. (1987). Utility of confirmatory factor analysis in test validation research. *Journal of Consulting and Clinical Psychology*, *55*(4), 584-594.

Collins, L. M., Murphy, S. A., & Bierman, K. L. (2004). A conceptual framework for adaptive preventive interventions. *Prevention Science*, *5*(3), 185-196.

De Los Reyes, A., & Kazdin, A. E. (2005). Informant discrepancies in the assessment of childhood psychopathology: A critical review, theoretical framework, and recommendations for further study. *Psychological Bulletin, 131*(4), 483-509.

De Los Reyes, A. (2011). Introduction to the special section: More than measurement error: Discovering meaning behind informant discrepancies in clinical assessments of children and adolescents. *Journal of Clinical Child & Adolescent Psychology*, *40*(1), 1-9.

Dirks, M. A., De Los Reyes, A., Briggs-Gowan, M., Cella, D., & Wakschlag, L. S. (2012). Annual Research Review: Embracing not erasing contextual variability in children's behavior–theory and utility in the selection and use of methods and informants in developmental psychopathology. *Journal of Child Psychology and Psychiatry*, *53*(5), 558-574.

Doty, D. H., & Glick, W. H. (1998). Common methods bias: does common methods variance really bias results? *Organizational Research Methods*, *1*(4), 374-406.

Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. *Psychological Methods*, *12*(1), 1-22.

Eid, M. E., & Diener, E. E. (2006). *Handbook of multimethod measurement in psychology*. Washington, DC, US: American Psychological Association.

Eid, M. (2000). A multitrait-multimethod model with minimal assumptions. *Psychometrika, 65,* 241-261.

Eid, M., Nussbeck, F. W., Geiser, C., Cole, D. A., Gollwitzer, M., & Lischetzke, T. (2008). Structural equation modeling of multitrait-multimethod data: Different models for different types of methods. *Psychological Methods*, *13*(3), 230-253.

Eid, M., Lischetzke, T., Nussbeck, F. W., & Trierweiler, L. I. (2003). Separating trait effects from trait-specific method effects in multitrait-multimethod models: A multiple-indicator CT-C(*M*-1) model. *Psychological Methods*, *8*, 38-60. doi: 10.1037/1082-989X.8.1.38

Eid, M., Geiser, C., & Koch, T. (2016). Measuring method effects: From traditional to design-oriented approaches. *Current Directions in Psychological Science, 25*(4), 275-280.

Eid, M., Lischetzke, T., & Nussbeck, F. W. (2006). Structural equation models for multitrait–multimethod data. In M. Eid & E. Diener (Eds.), *Handbook of multimethod measurement in psychology* (pp. 283–299). Washington, DC: American Psychological Association.

Eid, M., Nussbeck, F. W., Geiser, C., Cole, D. A., Gollwitzer, M., & Lischetzke, T. (2008). Structural equation modeling of multitrait-multimethod data: Different models for different types of methods. *Psychological Methods, 13*, 230-253. doi: 10.1037/a0013219

Evans, M. G. (1985). A Monte Carlo study of the effects of correlated method variance in moderated multiple regression analysis. *Organization Behavior and Human Decision Processes, 36*(3), 305-323.

Fiske, D. W. & Campbell, D. T. (1992). Citations do not solve problems. *Psychological Bulletin, 112*(3), 393-395.

Fiske, D. W. (1982). Convergent-discriminant validation in measurements and research strategies. *New Directions for Methodology of Social & Behavioral Science, 12*, 77-92.

Frazier, T. W., Youngstrom, E. A., Glutting, J. J., & Watkins, M. W. (2007). ADHD and achievement: Meta-analysis of the child, adolescent, and adult literatures and a concomitant study with college students. *Journal of Learning Disabilities*, *40*(1), 49-65.

Fritz, M. S., & MacKinnon, D. P. (2007). Required sample size to detect the mediated effect. *Psychological Science*, *18*(3), 233-239.

Fritz, M. S., Kenny, D. A., & MacKinnon, D. P. (2016). The combined effects of measurement error and omitting confounders in the single-mediator model. *Multivariate Behavioral Research*. doi: 10.1080/0027317.2016.1224154

Geiser, C., Bishop, J., & Lockhart, G. (2015). Collapsing factors in multitrait-multimethod models: examining consequences of a mismatch between measurement design and model. *Frontiers in Psychology*, *6*, 946.

Geiser, C., Koch, T., & Eid, M. (2014). Data-generating mechanisms versus constructively defined latent variables in multitrait–multimethod analysis: A comment on Castro-Schilo, Widaman, and Grimm (2013). *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(4), 509-523.

Gonzalez, O., & MacKinnon, D. P. (2018). A bifactor approach to model multifaceted constructs in statistical mediation analysis. *Educational and Psychological Measurement*, *78*(1), 5-31.

Hallquist, M., & Wiley, J. (2015). *MplusAutomation: Automating Mplus model estimation and interpretation: R package Version 0.6-3*. Retrieved from http://CRAN.R-project.org/package=MplusAutomation

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York: Guilford Press.

Hayes, A. F. (2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, *50*(1), 1-22.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication Monographs, 76*(4), 408-420. doi: 10.1080/03637750903310360

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York: Guilford Press.

Helm, J. L., Castro-Schilo, L., & Oravecz, Z. (2017). Bayesian versus maximum likelihood estimation of multitrait–multimethod confirmatory factor models. *Structural Equation Modeling: A Multidisciplinary Journal*, *24*(1), 17-30.

Hopwood, C. J., & Bornstein, R. F. (2014). *Multimethod clinical assessment.* New York: Guilford Press.

Hoyle, R. H., & Kenny, D. A. (1999). Sample size, reliability, and tests of statistical mediation. In R. H. Hoyle (Ed.), *Statistical strategies for small sample research* (pp. 195-222). London: SAGE Publications.

Jöreskog, K. G. (1971). Statistical analysis of sets of congeneric tests. *Psychometrika*, *36*, 109–133.

Kenny, D. A., & Judd, C. M. (1984). Estimating the nonlinear and interactive effects of latent variables. *Psychological Bulletin*, *96*(1), 201-210.

Kenny, D. A., & Kashy, D. A. (1992). Analysis of the multitrait-multimethod matrix by confirmatory factor analysis. *Psychological Bulletin, 112*(1), 165-172.

Kenny, D. A. (1976). An empirical application of confirmatory factor analysis to the multitrait-multimethod matrix. *Journal of Experimental Social Psychology, 12*(3), 247-252.

Klein, A., & Moosbrugger, H. (2000). Maximum likelihood estimation of latent interaction effects with the LMS method. *Psychometrika, 65*(4), 457-474.

Koch, T., Schultze, M., Burrus, J., Roberts, R. D., & Eid, M. (2015). A multilevel CFA-MTMM model for nested structurally different methods. *Journal of Educational and Behavioral Statistics*, *40*(5), 477-510.

Kochanska, G., Barry, R. A., Stellern, S. A., & O'Bleness, J. J. (2009). Early attachment organization moderates the parent–child mutually coercive pathway to children's antisocial conduct. *Child Development*, *80*(4), 1288-1300.

Lau, R. S., & Cheung, G. W. (2012). Estimating and comparing specific mediation effects in complex latent variable models. *Organizational Research Methods, 15*(1), 3-16, doi: 1094428110391673.

Ledgerwood, A., & Shrout, P. E. (2011). The trade-off between accuracy and precision in latent variable models of mediation processes. *Journal of Personality and Social Psychology*, *101*(6), 1174.

Litson, K., Geiser, C., Burns, G. L., & Servera, M. (2018). Trait and state variance in multi-informant assessments of ADHD and academic impairment in Spanish first-grade children. *Journal of Clinical Child & Adolescent Psychology*, *47*(5), 699-712.

Little, T. D., Rhemtulla, M., Gibson, K., & Schoemann, A. M. (2013). Why the items versus parcels controversy needn't be one. *Psychological Methods, 18*(3), 285-300.

Lord, F. M., & Novick, M. R. (1968). *Statistical theories of mental test scores*. Reading, MA: Addison-Wesley.

Lúcio, P. S., Salum, G. A., Rohde, L. A., Swardfager, W., Gadelha, A., Vandekerckhove, J., ... & Mari, J. J. (2016). Poor stimulus discriminability as a common neuropsychological deficit between ADHD and reading ability in young children: A moderated mediation model. *Psychological Medicine, 47*(2), 255-266.

Maas, C. J. M., Lensvelt-Mulders, G. J. L. M., & Hox, J. J. (2009). A multilevel multitrait-multimethod analysis. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 5*(3), 72-77.

MacKinnon, D. P., & Dwyer, J. H. (1993). Estimating mediated effects in prevention studies. *Evaluation Review, 17*(2), 144-158.

MacKinnon, D. P., & Fairchild, A. J. (2009). Current directions in mediation analysis. *Current Directions in Psychological Science*, *18*(1), 16-20.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological Methods*, *7*(1), 83.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research*, *39*(1), 99-128.

MacKinnon, D. P. (2008). *Introduction to statistical mediation analysis*. New York: Routledge.

MacKinnon, D. P., Coxe, S., & Baraldi, A. N. (2012). Guidelines for the investigation of mediating variables in business research. *Journal of Business and Psychology*, *27*(1), 1-14.

MacKinnon, D.P., Lockhart, G., Baraldi, A., & Gelfand, L. (2013). Evaluating treatment mediators and moderators. In J. S. Comer & P. C. Kendall (Eds.), *The Oxford handbook of research strategies for clinical psychology* (pp. 262-286). New York: Oxford University Press.

Marsh, H. W. (1989). Confirmatory factor analyses of multitrait-multimethod data: Many problems and a few solutions. *Applied Psychological Measurement*, *13*(4), 335-361.

Martin, A. J. (2014). Academic buoyancy and academic outcomes: Towards a further understanding of students with attention-deficit/hyperactivity disorder (ADHD), students without ADHD, and academic buoyancy itself. *British Journal of Educational Psychology*, *84*(1), 86-107.

Maslowsky, J., Jager, J., & Hemken, D. (2015). Estimating and interpreting latent variable interactions: A tutorial for applying the latent moderated structural equations method. *International Journal of Behavioral Development*, *39*(1), 87-96.

Massetti, G. M., Lahey, B. B., Pelham, W. E., Loney, J., Ehrhardt, A., Lee, S. S., & Kipp, H. (2008). Academic achievement over 8 years among children who met modified criteria for attention-deficit/hyperactivity disorder at 4–6 years of age. *Journal of Abnormal Child Psychology*, *36*(3), 399-410.

Meyer, G. J., Finn, S. E., Eyde, L. D., Kay, G. G., Moreland, K. L., Dies, R. R., ... & Reed, G. M. (2001). Psychological testing and psychological assessment: A review of evidence and issues. *American Psychologist*, *56*(2), 128-165.

Moosbrugger, H., Schermelleh-Engel, K., & Klein, A. (1997). Methodological problems of estimating latent interaction effects. *Methods of Psychological Research Online*, *2*(2), 95-111.

Morris, A. S., Robinson, L. R., & Eisenberg, N. (2006). Applying a multimethod perspective to the study of developmental psychology. In Eid, M. & Diener, E. (Eds.) *Handbook of multimethod measurement in psychology* (pp. 553). US: American Psychological Association.

Muthén, L.K. and Muthén, B.O. (1998-2018). *Mplus User's Guide.* Eighth Edition. Los Angeles, CA: Muthén & Muthén.

Muthén, L. K., & Muthén, B. O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling*, *9*(4), 599-620.

Muthén, B., & Asparouhov, T. (2012). Latent variable interactions. *Unpublished manuscript.* Retrieved from http://statmodel2.com/download/Latent%20variable%20interactions.pdf.

Novick, M. R. (1966). The axioms and principal results of classical test theory. *Journal of Mathematical Psychology, 3*, 1-18.

Nussbeck, F. W., Eid, M., Geiser, C., Courvoisier, D. S., & Lischetzke, T. (2009). A CTC (M− 1) model for different types of raters. *Methodology*, *5*(3), 88-98.

Pakula, B., Carpiano, R. M., Ratner, P. A., & Shoveller, J. A. (2016). Life stress as a mediator and community belonging as a moderator of mood and anxiety disorders and co-occurring disorders with heavy drinking of gay, lesbian, bisexual, and heterosexual Canadians. *Social Psychiatry and Psychiatric Epidemiology*, *51*(8), 1181-1192.

Papa, L., Litson, K., Lockhart, G., Chassin, L., & Geiser, C. (2015). Analyzing mediation models with multiple informants: A new approach and its application in clinical psychology. *Frontiers in Psychology: Psychology for Clinical Settings, 6*, 1674. doi: 10.3389/fpsyg.2015.01674.

Paxton, P., Curran, P. J., Bollen, K. A., Kirby, J., & Chen, F. (2001). Monte Carlo experiments: Design and implementation. *Structural Equation Modeling, 8*(2), 287-312. doi:10.1207/S15328007SEM0802_7

Pearl, J. (2009). *Causality* (Second Edition). New York, NY: Cambridge University Press.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*, 539-569.

Podsakoff, P. M., MacKenzie, S. B., Lee, J., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903.

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research, 42*(1). 185-227. doi: 10.108/00273170701341316

Preszler, J., Burns, G. L., Litson, K., Geiser, C., & Servera, M. (2017). Trait and state variance in oppositional defiant disorder symptoms: A multi-source investigation with Spanish children. *Psychological Assessment*, *29*(2), 135-147.

Schmitt, N., & Stults, D. M. (1986). Methodology review: Analysis of multitrait-multimethod matrices. *Applied Psychological Measurement*, *10*(1), 1-22.

Schultze, M., Koch, T., & Eid, M. (2015). The effects of nonindependent rater sets in multilevel–multitrait–multimethod models. *Structural Equation Modeling: A Multidisciplinary Journal*, *22*(3), 439-448.

Selig, J. P., & Preacher, K. J. (2009). Mediation models for longitudinal data in developmental research. *Research in Human Development, 6*(2-3), 144-164. doi: 10.1080/15427600902911247

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*, *13*, 290-312.

Stine, R. (1989). An introduction to bootstrap methods: Examples and ideas. *Sociological Methods & Research*, *18*(2-3), 243-291.

The University of Utah (2016). *CHPC – Research Computing Support for the University*. Retrieved from https://www.chpc.utah.edu/

Thoemmes, F., MacKinnon, D. P., & Reiser, M. R. (2010). Power analysis for complex mediational designs using Monte Carlo methods. *Structural Equation Modeling*, *17*(3), 510-534.

Volpe, R. J., DuPaul, G. J., DiPerna, J. C., Jitendra, A. K., Lutz, J. G., Tresco, K., & Junod, R. V. (2006). Attention deficit hyperactivity disorder and scholastic achievement: A model of mediation via academic enablers. *School Psychology Review*, *35*(1), 47-61.

Widaman, K. F. (1985). Hierarchically nested covariance structure models for multitrait-multimethod data. *Applied Psychological Measurement*, *9*, 1-26.

Williams, J., & MacKinnon, D. P. (2008). Resampling and distribution of the product methods for testing indirect effects in complex models. *Structural Equation Modeling*, *15*(1), 23-51.

Yuan, Y., & MacKinnon, D. P. (2009). Bayesian mediation analysis. *Psychological Methods*, *14*(4), 301.

Appendix

## Appendix A: Items used in the CADBI (Burns et al., 2010)

Academic impairment (AI) items

| | Please circle the answer that best describes your son's or daughter's behavior in comparison to others the same age | Severe Difficulty | Moderate Difficulty | Slight Difficulty | Average Performance for Grade Level | Slightly Above Average | Moderately Above Average | Excellent Performance |
|---|---|---|---|---|---|---|---|---|
| 1 | Completion of Homework Assignments | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 2 | Reading Skills | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 3 | Arithmetic Skills | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| 4 | Writing Skills | 0 | 1 | 2 | 3 | 4 | 5 | 6 |

Hyperactivity/impulsivity (HI) items

*The occurrence of these nine behaviors (items 1 to 9) is NOT due to oppositional behavior, defiance, anger, hostility or a failure to understand the task or the instructions.*

| | Please circle the answer that indicates how often the behavior has occurred in the last month. | Almost Never (Never or about once per month) | Seldom (about once per week) | Sometimes (several times per week) | Often (about once per day) | Very Often (several times per day) | Almost Always (many times per day) |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **1** | **Fidgets with or taps hands or feet or squirms in seat** | 0 | 1 | 2 | 3 | 4 | 5 |
| **2** | **Seems restless during activities when others are seated** (e.g., leaves his or her seat in the settings when remaining seated is expected) | 0 | 1 | 2 | 3 | 4 | 5 |
| **3** | **Runs about or climbs on things when it is inappropriate to do so** (e.g., moves excessively when not appropriate; adolescents may report excessive feelings of restlessness) | 0 | 1 | 2 | 3 | 4 | 5 |
| **4** | **Too loud or noisy during activities at home** | 0 | 1 | 2 | 3 | 4 | 5 |
| **5** | **Acts as if "driven by motor" or seems "on the go" during home activities** (e.g., unable to be still or uncomfortable being still for an extended time; appears restless; difficult to keep up with) | 0 | 1 | 2 | 3 | 4 | 5 |
| **6** | **Talks too much** (e.g., talks excessively at home) | 0 | 1 | 2 | 3 | 4 | 5 |
| **7** | **Blurts out an answer before the question is completed in home activities** (e.g., completes others' sentences; can't wait turn in conversations) | 0 | 1 | 2 | 3 | 4 | 5 |
| **8** | **Has difficulty waiting turn in home activities** (e.g., games; waiting in lines; family activities) | 0 | 1 | 2 | 3 | 4 | 5 |
| **9** | **Interrupts or intrudes on others** (e.g., butts into others' games or conversations; starts using others things without permission; intrudes into or takes over what others are doing) | 0 | 1 | 2 | 3 | 4 | 5 |

From Burns et al., 2014 on the creation of parcels:

"HI Parcel 1 involved the restless (leaves seat), too loud, blurts symptoms; HI Parcel 2 moves excessively, talks too much, and awaiting turn symptoms; and HI Parcel 3 fidgets/squirms, driven/on the go, and interrupts/intrudes symptoms."

Oppositional defiant disorder (ODD) items and parcels (from Preszler et al., 2016)

Parcel 1

1. Spiteful or vindictive toward adults (e.g., says mean things to hurt adults' feelings or does mean things to get back at adults)
2. Spiteful or vindictive toward siblings/peers (e.g., says mean things to hurt siblings/peers' feelings or does mean things to get back at siblings/peers
3. Argues with adults
4. Argues with siblings/peers
5. Actively defies or refuses to obey adults' requests or rules
6. Refuses to cooperate with reasonable requests from siblings/peers

Parcel 2

1. Annoys adults on purpose
2. Annoys siblings/peers on purpose
3. Becomes annoyed or irritated by the behavior of adults
4. Becomes annoyed or irritated by the behavior of siblings/peers
5. Appears angry or resentful toward adults

Parcel 3

1. Loses temper with adults when doesn't get own way
2. Loses temper with siblings/peers when doesn't get own way
3. Blames adults for his or her own mistakes or misbehavior
4. Blames peers for his or her own mistakes or misbehavior
5. Appears angry or resentful toward siblings/peer

## Appendix B: Mplus Syntax for Figures from Chapter IV

### Mplus Syntax for Figure 3.1

```
Title:      Non-indicator-specific STMM Model for HI

Data:       file is T1T3T4 Kaylee moms dads.dat;

Define:     ! reverse key the four academic items moms
            rM1_AS1 = 6 - M1_AS1; rM1_AS2 = 6 - M1_AS2;
            rM1_AS3 = 6 - M1_AS3; rM1_AS4 = 6 - M1_AS4;
            rM3_AS1 = 6 - M3_AS1; rM3_AS2 = 6 - M3_AS2;
            rM3_AS3 = 6 - M3_AS3; rM3_AS4 = 6 - M3_AS4;
            rM4_AS1 = 6 - M4_AS1; rM4_AS2 = 6 - M4_AS2;
            rM4_AS3 = 6 - M4_AS3; rM4_AS4 = 6 - M4_AS4;

            ! create the three indicators for AI moms
            AI1momt1= mean (rM1_AS1 rM1_AS2);
            AI2momt1= (rM1_AS3); AI3momt1= (rM1_AS4);
            AI1momt3= mean (rM3_AS1 rM3_AS2);
            AI2momt3= (rM3_AS3); AI3momt3= (rM3_AS4);
            AI1momt4= mean (rM4_AS1 rM4_AS2);
            AI2momt4= (rM4_AS3); AI3momt4= (rM4_AS4);

            ! reverse key codes for academic items dads
            rF1_AS1 = 6 - F1_AS1; rF1_AS2 = 6 - F1_AS2;
            rF1_AS3 = 6 - F1_AS3; rF1_AS4 = 6 - F1_AS4;
            rF3_AS1 = 6 - F3_AS1; rF3_AS2 = 6 - F3_AS2;
            rF3_AS3 = 6 - F3_AS3; rF3_AS4 = 6 - F3_AS4;
            rF4_AS1 = 6 - F4_AS1; rF4_AS2 = 6 - F4_AS2;
            rF4_AS3 = 6 - F4_AS3; rF4_AS4 = 6 - F4_AS4;

            ! create the three indicators for AI dads
            AI1dadt1= mean (rF1_AS1 rF1_AS2);
            AI2dadt1= (rF1_AS3); AI3dadt1= (rF1_AS4);
            AI1dadt3= mean (rF3_AS1 rF3_AS2);
            AI2dadt3= (rF3_AS3); AI3dadt3= (rF3_AS4);
            AI1dadt4= mean (rF4_AS1 rF4_AS2);
            AI2dadt4= (rF4_AS3); AI3dadt4= (rF4_AS4);

Variable:   Names are code schools sex classrm M1_AS1
            M1_AS2 M1_AS3 M1_AS4 M1_SC1 M1_SC2 M1_SC3
            M1_SC4 M1_SC5 M1_SC6 M1_SC7 M1_SC8 F1_AS1
            F1_AS2 F1_AS3 F1_AS4 F1_SC1 F1_SC2 F1_SC3
```

```
            F1_SC4 F1_SC5 F1_SC6 F1_SC7 F1_SC8 M3_AS1
            M3_AS2 M3_AS3 M3_AS4 M3_SC1 M3_SC2 M3_SC3
            M3_SC4 M3_SC5 M3_SC6 M3_SC7 M3_SC8 F3_AS1
            F3_AS2 F3_AS3 F3_AS4 F3_SC1 F3_SC2 F3_SC3
            F3_SC4 F3_SC5 F3_SC6 F3_SC7 F3_SC8 F4_SC1
            F4_SC2 F4_SC3 F4_SC4 F4_AS1 F4_AS2 F4_AS3
            F4_AS4 M4_SC1 M4_SC2 M4_SC3 M4_SC4 M4_AS1
            M4_AS2 M4_AS3 M4_AS4 IN1momT1 IN2momT1 IN3momT1
            HI1momT1 HI2momT1 HI3momT1 OD1momT1 OD2momT1
            OD3momT1 IN1dadT1 IN2dadT1 IN3dadT1 HI1dadT1
            HI2dadT1 HI3dadT1 OD1dadT1 OD2dadT1 OD3dadT1
            IN1momT3 IN2momT3 IN3momT3 HI1momT3 HI2momT3
            HI3momT3 OD1momT3 OD2momT3 OD3momT3 IN1dadT3
            IN2dadT3 IN3dadT3 HI1dadT3 HI2dadT3 HI3dadT3
            OD1dadT3 OD2dadT3 OD3dadT3 IN1momT4 IN2momT4
            IN3momT4 HI1momT4 HI2momT4 HI3momT4 OD1momT4
            OD2momT4 OD3momT4 IN1dadT4 IN2dadT4 IN3dadT4
            HI1dadT4 HI2dadT4 HI3dadT4 OD1dadT4 OD2dadT4
            OD3dadT4MT1_CE1 MT1_CE2 MT1_CE3 MT1_CE4 FT1_CE1
            FT1_CE2 FT1_CE3 FT1_CE4 MT3_CE1 MT3_CE2 MT3_CE3
            MT3_CE4 FT3_CE1 FT3_CE2 FT3_CE3 FT3_CE4 FT4_CE1
            FT4_CE2 FT4_CE3 FT4_CE4 MT4_CE1 MT4_CE2 MT4_CE3
            MT4_CE4;

            Missing are . ;

            Usevariables are HI1momT1 HI1dadT1 HI2momT1
            HI2dadT1 HI3momT1 HI3dadT1;

Analysis:   estimator = MLR;

Model:      HI1t1 by HI1momT1 HI1dadT1 HI2momT1
                     HI2dadT1 HI3momT1 HI3dadT1; !Trait

            HIdadt1 by HI1dadT1 HI2dadT1 HI3dadT1; !Method

            HIdadt1 with HI1t1@0; !no corr between T and M

Output:     sampstat stdyx;
```

**Mplus Syntax for Figure 3.2**

```
Title:      Indicator-specific STMM Model for HI
```

```
Data:       file is T1T3T4 Kaylee moms dads.dat;

Define:     ! reverse key the four academic items moms
            rM1_AS1 = 6 - M1_AS1; rM1_AS2 = 6 - M1_AS2;
            rM1_AS3 = 6 - M1_AS3; rM1_AS4 = 6 - M1_AS4;
            rM3_AS1 = 6 - M3_AS1; rM3_AS2 = 6 - M3_AS2;
            rM3_AS3 = 6 - M3_AS3; rM3_AS4 = 6 - M3_AS4;
            rM4_AS1 = 6 - M4_AS1; rM4_AS2 = 6 - M4_AS2;
            rM4_AS3 = 6 - M4_AS3; rM4_AS4 = 6 - M4_AS4;

            ! create the three indicators for AI moms
            AI1momt1= mean (rM1_AS1 rM1_AS2);
            AI2momt1= (rM1_AS3); AI3momt1= (rM1_AS4);
            AI1momt3= mean (rM3_AS1 rM3_AS2);
            AI2momt3= (rM3_AS3); AI3momt3= (rM3_AS4);
            AI1momt4= mean (rM4_AS1 rM4_AS2);
            AI2momt4= (rM4_AS3); AI3momt4= (rM4_AS4);

            ! reverse key codes for academic items dads
            rF1_AS1 = 6 - F1_AS1; rF1_AS2 = 6 - F1_AS2;
            rF1_AS3 = 6 - F1_AS3; rF1_AS4 = 6 - F1_AS4;
            rF3_AS1 = 6 - F3_AS1; rF3_AS2 = 6 - F3_AS2;
            rF3_AS3 = 6 - F3_AS3; rF3_AS4 = 6 - F3_AS4;
            rF4_AS1 = 6 - F4_AS1; rF4_AS2 = 6 - F4_AS2;
            rF4_AS3 = 6 - F4_AS3; rF4_AS4 = 6 - F4_AS4;

            ! create the three indicators for AI dads
            AI1dadt1= mean (rF1_AS1 rF1_AS2);
            AI2dadt1= (rF1_AS3); AI3dadt1= (rF1_AS4);
            AI1dadt3= mean (rF3_AS1 rF3_AS2);
            AI2dadt3= (rF3_AS3); AI3dadt3= (rF3_AS4);
            AI1dadt4= mean (rF4_AS1 rF4_AS2);
            AI2dadt4= (rF4_AS3); AI3dadt4= (rF4_AS4);

Variable:   Names are code schools sex classrm M1_AS1
            M1_AS2 M1_AS3 M1_AS4 M1_SC1 M1_SC2 M1_SC3
            M1_SC4 M1_SC5 M1_SC6 M1_SC7 M1_SC8 F1_AS1
            F1_AS2 F1_AS3 F1_AS4 F1_SC1 F1_SC2 F1_SC3
            F1_SC4 F1_SC5 F1_SC6 F1_SC7 F1_SC8 M3_AS1
            M3_AS2 M3_AS3 M3_AS4 M3_SC1 M3_SC2 M3_SC3
            M3_SC4 M3_SC5 M3_SC6 M3_SC7 M3_SC8 F3_AS1
            F3_AS2 F3_AS3 F3_AS4 F3_SC1 F3_SC2 F3_SC3
            F3_SC4 F3_SC5 F3_SC6 F3_SC7 F3_SC8 F4_SC1
            F4_SC2 F4_SC3 F4_SC4 F4_AS1 F4_AS2 F4_AS3
```

```
            F4_AS4 M4_SC1 M4_SC2 M4_SC3 M4_SC4 M4_AS1
            M4_AS2 M4_AS3 M4_AS4 IN1momT1 IN2momT1 IN3momT1
            HI1momT1 HI2momT1 HI3momT1 OD1momT1 OD2momT1
            OD3momT1 IN1dadT1 IN2dadT1 IN3dadT1 HI1dadT1
            HI2dadT1 HI3dadT1 OD1dadT1 OD2dadT1 OD3dadT1
            IN1momT3 IN2momT3 IN3momT3 HI1momT3 HI2momT3
            HI3momT3 OD1momT3 OD2momT3 OD3momT3 IN1dadT3
            IN2dadT3 IN3dadT3 HI1dadT3 HI2dadT3 HI3dadT3
            OD1dadT3 OD2dadT3 OD3dadT3 IN1momT4 IN2momT4
            IN3momT4 HI1momT4 HI2momT4 HI3momT4 OD1momT4
            OD2momT4 OD3momT4 IN1dadT4 IN2dadT4 IN3dadT4
            HI1dadT4 HI2dadT4 HI3dadT4 OD1dadT4 OD2dadT4
            OD3dadT4MT1_CE1 MT1_CE2 MT1_CE3 MT1_CE4 FT1_CE1
            FT1_CE2 FT1_CE3 FT1_CE4 MT3_CE1 MT3_CE2 MT3_CE3
            MT3_CE4 FT3_CE1 FT3_CE2 FT3_CE3 FT3_CE4 FT4_CE1
            FT4_CE2 FT4_CE3 FT4_CE4 MT4_CE1 MT4_CE2 MT4_CE3
            MT4_CE4;

            Missing are . ;

            Usevariables are HI1momT1 HI1dadT1 HI2momT1
            HI2dadT1 HI3momT1 HI3dadT1;

Analysis:   estimator = MLR;

Model:      HI1t1 by HI1momT1 HI1dadT1;
            HI2t1 by HI2momT1 HI2dadT1;
            HI3t1 by HI3momT1 HI3dadT1; !Trait

            HIdadt1 by HI1dadT1 HI2dadT1 HI3dadT1; !Method

            HIdadt1 with HI1t1@0 HI2t1@0 HI3t1@0;

Output:     sampstat stdyx;
```

**Mplus Syntax for Figure 3.3**

```
Title:      Indicator-specific CT-C(M-1) Model for HI, IN,
            OD, AI

Data:       file is T1T3T4 Kaylee moms dads.dat;

Define:     ! reverse key the four academic items moms
```

```
rM1_AS1 = 6 - M1_AS1; rM1_AS2 = 6 - M1_AS2;
rM1_AS3 = 6 - M1_AS3; rM1_AS4 = 6 - M1_AS4;
rM3_AS1 = 6 - M3_AS1; rM3_AS2 = 6 - M3_AS2;
rM3_AS3 = 6 - M3_AS3; rM3_AS4 = 6 - M3_AS4;
rM4_AS1 = 6 - M4_AS1; rM4_AS2 = 6 - M4_AS2;
rM4_AS3 = 6 - M4_AS3; rM4_AS4 = 6 - M4_AS4;

! create the three indicators for AI moms
AI1momt1= mean (rM1_AS1 rM1_AS2);
AI2momt1= (rM1_AS3); AI3momt1= (rM1_AS4);
AI1momt3= mean (rM3_AS1 rM3_AS2);
AI2momt3= (rM3_AS3); AI3momt3= (rM3_AS4);
AI1momt4= mean (rM4_AS1 rM4_AS2);
AI2momt4= (rM4_AS3); AI3momt4= (rM4_AS4);

! reverse key codes for academic items dads
rF1_AS1 = 6 - F1_AS1; rF1_AS2 = 6 - F1_AS2;
rF1_AS3 = 6 - F1_AS3; rF1_AS4 = 6 - F1_AS4;
rF3_AS1 = 6 - F3_AS1; rF3_AS2 = 6 - F3_AS2;
rF3_AS3 = 6 - F3_AS3; rF3_AS4 = 6 - F3_AS4;
rF4_AS1 = 6 - F4_AS1; rF4_AS2 = 6 - F4_AS2;
rF4_AS3 = 6 - F4_AS3; rF4_AS4 = 6 - F4_AS4;

! create the three indicators for AI dads
AI1dadt1= mean (rF1_AS1 rF1_AS2);
AI2dadt1= (rF1_AS3); AI3dadt1= (rF1_AS4);
AI1dadt3= mean (rF3_AS1 rF3_AS2);
AI2dadt3= (rF3_AS3); AI3dadt3= (rF3_AS4);
AI1dadt4= mean (rF4_AS1 rF4_AS2);
AI2dadt4= (rF4_AS3); AI3dadt4= (rF4_AS4);

Variable:  Names are code schools sex classrm M1_AS1
           M1_AS2 M1_AS3 M1_AS4 M1_SC1 M1_SC2 M1_SC3
           M1_SC4 M1_SC5 M1_SC6 M1_SC7 M1_SC8 F1_AS1
           F1_AS2 F1_AS3 F1_AS4 F1_SC1 F1_SC2 F1_SC3
           F1_SC4 F1_SC5 F1_SC6 F1_SC7 F1_SC8 M3_AS1
           M3_AS2 M3_AS3 M3_AS4 M3_SC1 M3_SC2 M3_SC3
           M3_SC4 M3_SC5 M3_SC6 M3_SC7 M3_SC8 F3_AS1
           F3_AS2 F3_AS3 F3_AS4 F3_SC1 F3_SC2 F3_SC3
           F3_SC4 F3_SC5 F3_SC6 F3_SC7 F3_SC8 F4_SC1
           F4_SC2 F4_SC3 F4_SC4 F4_AS1 F4_AS2 F4_AS3
           F4_AS4 M4_SC1 M4_SC2 M4_SC3 M4_SC4 M4_AS1
           M4_AS2 M4_AS3 M4_AS4 IN1momT1 IN2momT1 IN3momT1
           HI1momT1 HI2momT1 HI3momT1 OD1momT1 OD2momT1
           OD3momT1 IN1dadT1 IN2dadT1 IN3dadT1 HI1dadT1
```

```
            HI2dadT1 HI3dadT1 OD1dadT1 OD2dadT1 OD3dadT1
            IN1momT3 IN2momT3 IN3momT3 HI1momT3 HI2momT3
            HI3momT3 OD1momT3 OD2momT3 OD3momT3 IN1dadT3
            IN2dadT3 IN3dadT3 HI1dadT3 HI2dadT3 HI3dadT3
            OD1dadT3 OD2dadT3 OD3dadT3 IN1momT4 IN2momT4
            IN3momT4 HI1momT4 HI2momT4 HI3momT4 OD1momT4
            OD2momT4 OD3momT4 IN1dadT4 IN2dadT4 IN3dadT4
            HI1dadT4 HI2dadT4 HI3dadT4 OD1dadT4 OD2dadT4
            OD3dadT4MT1_CE1 MT1_CE2 MT1_CE3 MT1_CE4 FT1_CE1
            FT1_CE2 FT1_CE3 FT1_CE4 MT3_CE1 MT3_CE2 MT3_CE3
            MT3_CE4 FT3_CE1 FT3_CE2 FT3_CE3 FT3_CE4 FT4_CE1
            FT4_CE2 FT4_CE3 FT4_CE4 MT4_CE1 MT4_CE2 MT4_CE3
            MT4_CE4;

            Missing are . ;

            Usevariables are HI1momT1 HI1dadT1 HI2momT1
            HI2dadT1 HI3momT1 HI3dadT1 IN1momT1 IN1dadT1
            IN2momT1 IN2dadT1 IN3momT1 IN3dadT1 OD1momT3
            OD1dadT3 OD2momT3 OD2dadT3 OD3momT3 OD3dadT3
            AI1momT4 AI1dadT4 AI2momT4 AI2dadT4 AI3momT4
            AI3dadT4;

Analysis:   estimator = ML;

Model:      !HI factor structure
            HI1t1 by HI1momT1 HI1dadT1;
            HI2t1 by HI2momT1 HI2dadT1;
            HI3t1 by HI3momT1 HI3dadT1;

            HIdadt1 by HI1dadT1 HI2dadT1 HI3dadT1;

            HIdadt1 with HI1t1@0 HI2t1@0 HI3t1@0;

            !IN factor structure
            IN1t1 by IN1momT1 IN1dadT1;
            IN2t1 by IN2momT1 IN2dadT1;
            IN3t1 by IN3momT1 IN3dadT1;

            INdadt1 by IN1dadT1 IN2dadT1 IN3dadT1;

            INdadt1 with IN1t1@0 IN2t1@0 IN3t1@0;

            !OD factor structure
            OD1t3 by OD1momT3 OD1dadT3;
```

```
            OD2t3 by OD2momT3 OD2dadT3;
            OD3t3 by OD3momT3 OD3dadT3;

            ODdadt3 by OD1dadT3 OD2dadT3 OD3dadT3;

            ODdadt3 with OD1t3@0 OD2t3@0 OD3t3@0;

            !AI factor structure
            AI1t4 by AI1momT4 AI1dadT4;
            AI2t4 by AI2momT4 AI2dadT4;
            AI3t4 by AI3momT4 AI3dadT4;

            AIdadt4 by AI1dadT4 AI2dadT4 AI3dadT4;

            AIdadt4 with AI1t4@0 AI2t4@0 AI3t4@0;

Output:     sampstat stdyx;
```

**Mplus Syntax for Figure 3.4**

```
Title:      Latent Means Indicator-specific CT-C(M-1) Model
            for HI, IN, OD, AI

Data:       file is T1T3T4 Kaylee moms dads.dat;

Define:     ! reverse key the four academic items moms
            rM1_AS1 = 6 - M1_AS1; rM1_AS2 = 6 - M1_AS2;
            rM1_AS3 = 6 - M1_AS3; rM1_AS4 = 6 - M1_AS4;
            rM3_AS1 = 6 - M3_AS1; rM3_AS2 = 6 - M3_AS2;
            rM3_AS3 = 6 - M3_AS3; rM3_AS4 = 6 - M3_AS4;
            rM4_AS1 = 6 - M4_AS1; rM4_AS2 = 6 - M4_AS2;
            rM4_AS3 = 6 - M4_AS3; rM4_AS4 = 6 - M4_AS4;

            ! create the three indicators for AI moms
            AI1momt1= mean (rM1_AS1 rM1_AS2);
            AI2momt1= (rM1_AS3); AI3momt1= (rM1_AS4);
            AI1momt3= mean (rM3_AS1 rM3_AS2);
            AI2momt3= (rM3_AS3); AI3momt3= (rM3_AS4);
            AI1momt4= mean (rM4_AS1 rM4_AS2);
            AI2momt4= (rM4_AS3); AI3momt4= (rM4_AS4);

            ! reverse key codes for academic items dads
```

```
rF1_AS1 = 6 - F1_AS1; rF1_AS2 = 6 - F1_AS2;
rF1_AS3 = 6 - F1_AS3; rF1_AS4 = 6 - F1_AS4;
rF3_AS1 = 6 - F3_AS1; rF3_AS2 = 6 - F3_AS2;
rF3_AS3 = 6 - F3_AS3; rF3_AS4 = 6 - F3_AS4;
rF4_AS1 = 6 - F4_AS1; rF4_AS2 = 6 - F4_AS2;
rF4_AS3 = 6 - F4_AS3; rF4_AS4 = 6 - F4_AS4;

! create the three indicators for AI dads
AI1dadt1= mean (rF1_AS1 rF1_AS2);
AI2dadt1= (rF1_AS3); AI3dadt1= (rF1_AS4);
AI1dadt3= mean (rF3_AS1 rF3_AS2);
AI2dadt3= (rF3_AS3); AI3dadt3= (rF3_AS4);
AI1dadt4= mean (rF4_AS1 rF4_AS2);
AI2dadt4= (rF4_AS3); AI3dadt4= (rF4_AS4);

Variable: Names are code schools sex classrm M1_AS1
          M1_AS2 M1_AS3 M1_AS4 M1_SC1 M1_SC2 M1_SC3
          M1_SC4 M1_SC5 M1_SC6 M1_SC7 M1_SC8 F1_AS1
          F1_AS2 F1_AS3 F1_AS4 F1_SC1 F1_SC2 F1_SC3
          F1_SC4 F1_SC5 F1_SC6 F1_SC7 F1_SC8 M3_AS1
          M3_AS2 M3_AS3 M3_AS4 M3_SC1 M3_SC2 M3_SC3
          M3_SC4 M3_SC5 M3_SC6 M3_SC7 M3_SC8 F3_AS1
          F3_AS2 F3_AS3 F3_AS4 F3_SC1 F3_SC2 F3_SC3
          F3_SC4 F3_SC5 F3_SC6 F3_SC7 F3_SC8 F4_SC1
          F4_SC2 F4_SC3 F4_SC4 F4_AS1 F4_AS2 F4_AS3
          F4_AS4 M4_SC1 M4_SC2 M4_SC3 M4_SC4 M4_AS1
          M4_AS2 M4_AS3 M4_AS4 IN1momT1 IN2momT1 IN3momT1
          HI1momT1 HI2momT1 HI3momT1 OD1momT1 OD2momT1
          OD3momT1 IN1dadT1 IN2dadT1 IN3dadT1 HI1dadT1
          HI2dadT1 HI3dadT1 OD1dadT1 OD2dadT1 OD3dadT1
          IN1momT3 IN2momT3 IN3momT3 HI1momT3 HI2momT3
          HI3momT3 OD1momT3 OD2momT3 OD3momT3 IN1dadT3
          IN2dadT3 IN3dadT3 HI1dadT3 HI2dadT3 HI3dadT3
          OD1dadT3 OD2dadT3 OD3dadT3 IN1momT4 IN2momT4
          IN3momT4 HI1momT4 HI2momT4 HI3momT4 OD1momT4
          OD2momT4 OD3momT4 IN1dadT4 IN2dadT4 IN3dadT4
          HI1dadT4 HI2dadT4 HI3dadT4 OD1dadT4 OD2dadT4
          OD3dadT4MT1_CE1 MT1_CE2 MT1_CE3 MT1_CE4 FT1_CE1
          FT1_CE2 FT1_CE3 FT1_CE4 MT3_CE1 MT3_CE2 MT3_CE3
          MT3_CE4 FT3_CE1 FT3_CE2 FT3_CE3 FT3_CE4 FT4_CE1
          FT4_CE2 FT4_CE3 FT4_CE4 MT4_CE1 MT4_CE2 MT4_CE3
          MT4_CE4;

          Missing are . ;
```

```
             Usevariables are HI1momT1 HI1dadT1 HI2momT1
             HI2dadT1 HI3momT1 HI3dadT1 IN1momT1 IN1dadT1
             IN2momT1 IN2dadT1 IN3momT1 IN3dadT1 OD1momT3
             OD1dadT3 OD2momT3 OD2dadT3 OD3momT3 OD3dadT3
             AI1momT4 AI1dadT4 AI2momT4 AI2dadT4 AI3momT4
             AI3dadT4;

Analysis:    estimator = ML;

Model:       !HI factor structure
             HI1t1 by HI1momT1 HI1dadT1;
             HI2t1 by HI2momT1 HI2dadT1;
             HI3t1 by HI3momT1 HI3dadT1;
                  !latent means approach
             HIt1 by HI1t1@1 HI2t1@1 HI3t1@1;
             MHI2 by HI1t1@-1 HI2t1@1;
             MHI3 by HI1t1@-1 HI3t1@1;
                  !no first-order residual variance allowed
             HI1t1@0 HI2t1@0 HI3t1@0;

             HIdadt1 by HI1dadT1 HI2dadT1 HI3dadT1;

             HIdadt1 with HI1t1@0 HI2t1@0 HI3t1@0;

             !IN factor structure
             IN1t1 by IN1momT1 IN1dadT1;
             IN2t1 by IN2momT1 IN2dadT1;
             IN3t1 by IN3momT1 IN3dadT1;
                  !latent means approach
             INt1 by IN1t1@1 IN2t1@1 IN3t1@1;
             MIN2 by IN1t1@-1 IN2t1@1;
             MIN3 by IN1t1@-1 IN3t1@1;
                  !no first-order residual variance allowed
             IN1t1@0 IN2t1@0 IN3t1@0;

             INdadt1 by IN1dadT1 IN2dadT1 IN3dadT1;

             INdadt1 with IN1t1@0 IN2t1@0 IN3t1@0;

             !OD factor structure
             OD1t3 by OD1momT3 OD1dadT3;
             OD2t3 by OD2momT3 OD2dadT3;
             OD3t3 by OD3momT3 OD3dadT3;
                  !latent means approach
             ODt3 by OD1T3@1 OD2T3@1 OD3T3@1;
```

```
MOD2 by OD1T3@-1 OD2T3@1;
MOD3 by OD1T3@-1 OD3T3@1;
     !no first-order residual variance allowed
OD1t3@0 OD2t3@0 OD3t3@0;

ODdadt3 by OD1dadT3 OD2dadT3 OD3dadT3;

ODdadt3 with OD1t3@0 OD2t3@0 OD3t3@0;

!AI factor structure
AI1t4 by AI1momT4 AI1dadT4;
AI2t4 by AI2momT4 AI2dadT4;
AI3t4 by AI3momT4 AI3dadT4;
     !latent means approach
AIt4 by AI1T4@1 AI2T4@1 AI3T4@1;
MAI2 by AI1T4@-1 AI2T4@1;
MAI3 by AI1T4@-1 AI3T4@1;
     !no first-order residual variance allowed
AI1t4@0 AI2t4@0 AI3t4@0;

AIdadt4 by AI1dadT4 AI2dadT4 AI3dadT4;

AIdadt4 with AI1t4@0 AI2t4@0 AI3t4@0;

!Unrestricting correlations
HIt1 INt1 ODt3 AIt4 with MHI2 MHI3 MIN2 MIN3
MOD2 MOD3 MAI2 MAI3;
HIt1 with INdadt1 ODdadt3 AIdadt4;
INt1 with HIdadt1 ODdadt3 AIdadt4;
ODt3 with HIdadt1 INdadt1 AIdadt4;
AIt4 with HIdadt1 INdadt1 ODdadt3;

!Restricting correlations
HIdadt1 with HIt1@0 MHI2@0 MHI3@0;
INdadt1 with INt1@0 MIN2@0 MIN3@0;
ODdadt3 with ODt3@0 MOD2@0 MOD3@0;
AIdadt4 with AIt4@0 MAI2@0 MAI3@0;

Output:    sampstat stdyx;
```

**Mplus Syntax for Figure 3.5**

```
Title:      M4 Model without the latent interaction term
            for HI, IN, OD, AI

Data:       file is T1T3T4 Kaylee moms dads.dat;

Define:     ! reverse key the four academic items moms
            rM1_AS1 = 6 - M1_AS1; rM1_AS2 = 6 - M1_AS2;
            rM1_AS3 = 6 - M1_AS3; rM1_AS4 = 6 - M1_AS4;
            rM3_AS1 = 6 - M3_AS1; rM3_AS2 = 6 - M3_AS2;
            rM3_AS3 = 6 - M3_AS3; rM3_AS4 = 6 - M3_AS4;
            rM4_AS1 = 6 - M4_AS1; rM4_AS2 = 6 - M4_AS2;
            rM4_AS3 = 6 - M4_AS3; rM4_AS4 = 6 - M4_AS4;

            ! create the three indicators for AI moms
            AI1momt1= mean (rM1_AS1 rM1_AS2);
            AI2momt1= (rM1_AS3); AI3momt1= (rM1_AS4);
            AI1momt3= mean (rM3_AS1 rM3_AS2);
            AI2momt3= (rM3_AS3); AI3momt3= (rM3_AS4);
            AI1momt4= mean (rM4_AS1 rM4_AS2);
            AI2momt4= (rM4_AS3); AI3momt4= (rM4_AS4);

            ! reverse key codes for academic items dads
            rF1_AS1 = 6 - F1_AS1; rF1_AS2 = 6 - F1_AS2;
            rF1_AS3 = 6 - F1_AS3; rF1_AS4 = 6 - F1_AS4;
            rF3_AS1 = 6 - F3_AS1; rF3_AS2 = 6 - F3_AS2;
            rF3_AS3 = 6 - F3_AS3; rF3_AS4 = 6 - F3_AS4;
            rF4_AS1 = 6 - F4_AS1; rF4_AS2 = 6 - F4_AS2;
            rF4_AS3 = 6 - F4_AS3; rF4_AS4 = 6 - F4_AS4;

            ! create the three indicators for AI dads
            AI1dadt1= mean (rF1_AS1 rF1_AS2);
            AI2dadt1= (rF1_AS3); AI3dadt1= (rF1_AS4);
            AI1dadt3= mean (rF3_AS1 rF3_AS2);
            AI2dadt3= (rF3_AS3); AI3dadt3= (rF3_AS4);
            AI1dadt4= mean (rF4_AS1 rF4_AS2);
            AI2dadt4= (rF4_AS3); AI3dadt4= (rF4_AS4);

Variable:   Names are code schools sex classrm M1_AS1
            M1_AS2 M1_AS3 M1_AS4 M1_SC1 M1_SC2 M1_SC3
            M1_SC4 M1_SC5 M1_SC6 M1_SC7 M1_SC8 F1_AS1
            F1_AS2 F1_AS3 F1_AS4 F1_SC1 F1_SC2 F1_SC3
            F1_SC4 F1_SC5 F1_SC6 F1_SC7 F1_SC8 M3_AS1
            M3_AS2 M3_AS3 M3_AS4 M3_SC1 M3_SC2 M3_SC3
            M3_SC4 M3_SC5 M3_SC6 M3_SC7 M3_SC8 F3_AS1
            F3_AS2 F3_AS3 F3_AS4 F3_SC1 F3_SC2 F3_SC3
```

```
                F3_SC4 F3_SC5 F3_SC6 F3_SC7 F3_SC8 F4_SC1
                F4_SC2 F4_SC3 F4_SC4 F4_AS1 F4_AS2 F4_AS3
                F4_AS4 M4_SC1 M4_SC2 M4_SC3 M4_SC4 M4_AS1
                M4_AS2 M4_AS3 M4_AS4 IN1momT1 IN2momT1 IN3momT1
                HI1momT1 HI2momT1 HI3momT1 OD1momT1 OD2momT1
                OD3momT1 IN1dadT1 IN2dadT1 IN3dadT1 HI1dadT1
                HI2dadT1 HI3dadT1 OD1dadT1 OD2dadT1 OD3dadT1
                IN1momT3 IN2momT3 IN3momT3 HI1momT3 HI2momT3
                HI3momT3 OD1momT3 OD2momT3 OD3momT3 IN1dadT3
                IN2dadT3 IN3dadT3 HI1dadT3 HI2dadT3 HI3dadT3
                OD1dadT3 OD2dadT3 OD3dadT3 IN1momT4 IN2momT4
                IN3momT4 HI1momT4 HI2momT4 HI3momT4 OD1momT4
                OD2momT4 OD3momT4 IN1dadT4 IN2dadT4 IN3dadT4
                HI1dadT4 HI2dadT4 HI3dadT4 OD1dadT4 OD2dadT4
                OD3dadT4MT1_CE1 MT1_CE2 MT1_CE3 MT1_CE4 FT1_CE1
                FT1_CE2 FT1_CE3 FT1_CE4 MT3_CE1 MT3_CE2 MT3_CE3
                MT3_CE4 FT3_CE1 FT3_CE2 FT3_CE3 FT3_CE4 FT4_CE1
                FT4_CE2 FT4_CE3 FT4_CE4 MT4_CE1 MT4_CE2 MT4_CE3
                MT4_CE4;

                Missing are . ;

                Usevariables are HI1momT1 HI1dadT1 HI2momT1
                HI2dadT1 HI3momT1 HI3dadT1 IN1momT1 IN1dadT1
                IN2momT1 IN2dadT1 IN3momT1 IN3dadT1 OD1momT3
                OD1dadT3 OD2momT3 OD2dadT3 OD3momT3 OD3dadT3
                AI1momT4 AI1dadT4 AI2momT4 AI2dadT4 AI3momT4
                AI3dadT4;

Analysis:       estimator = ML;

Model:          !HI factor structure
                HI1t1 by HI1momT1 HI1dadT1;
                HI2t1 by HI2momT1 HI2dadT1;
                HI3t1 by HI3momT1 HI3dadT1;
                     !latent means approach
                HIt1 by HI1t1@1 HI2t1@1 HI3t1@1;
                MHI2 by HI1t1@-1 HI2t1@1;
                MHI3 by HI1t1@-1 HI3t1@1;
                     !no first-order residual variance allowed
                HI1t1@0 HI2t1@0 HI3t1@0;

                HIdadt1 by HI1dadT1 HI2dadT1 HI3dadT1;

                HIdadt1 with HI1t1@0 HI2t1@0 HI3t1@0;
```

```
!IN factor structure
IN1t1 by IN1momT1 IN1dadT1;
IN2t1 by IN2momT1 IN2dadT1;
IN3t1 by IN3momT1 IN3dadT1;
     !latent means approach
INt1 by IN1t1@1 IN2t1@1 IN3t1@1;
MIN2 by IN1t1@-1 IN2t1@1;
MIN3 by IN1t1@-1 IN3t1@1;
     !no first-order residual variance allowed
IN1t1@0 IN2t1@0 IN3t1@0;

INdadt1 by IN1dadT1 IN2dadT1 IN3dadT1;

INdadt1 with IN1t1@0 IN2t1@0 IN3t1@0;

!OD factor structure
OD1t3 by OD1momT3 OD1dadT3;
OD2t3 by OD2momT3 OD2dadT3;
OD3t3 by OD3momT3 OD3dadT3;
     !latent means approach
ODt3 by OD1T3@1 OD2T3@1 OD3T3@1;
MOD2 by OD1T3@-1 OD2T3@1;
MOD3 by OD1T3@-1 OD3T3@1;
     !no first-order residual variance allowed
OD1t3@0 OD2t3@0 OD3t3@0;

ODdadt3 by OD1dadT3 OD2dadT3 OD3dadT3;

ODdadt3 with OD1t3@0 OD2t3@0 OD3t3@0;

!AI factor structure
AI1t4 by AI1momT4 AI1dadT4;
AI2t4 by AI2momT4 AI2dadT4;
AI3t4 by AI3momT4 AI3dadT4;
     !latent means approach
AIt4 by AI1T4@1 AI2T4@1 AI3T4@1;
MAI2 by AI1T4@-1 AI2T4@1;
MAI3 by AI1T4@-1 AI3T4@1;
     !no first-order residual variance allowed
AI1t4@0 AI2t4@0 AI3t4@0;

AIdadt4 by AI1dadT4 AI2dadT4 AI3dadT4;

AIdadt4 with AI1t4@0 AI2t4@0 AI3t4@0;
```

```
!Unrestricting correlations
HIt1 INt1 ODt3 AIt4 with MHI2 MHI3 MIN2 MIN3
MOD2 MOD3 MAI2 MAI3;
HIt1 with INdadt1 ODdadt3 AIdadt4;
INt1 with HIdadt1 ODdadt3 AIdadt4;
ODt3 with HIdadt1 INdadt1 AIdadt4;
AIt4 with HIdadt1 INdadt1 ODdadt3;

!Restricting correlations
HIdadt1 with HIt1@0 MHI2@0 MHI3@0;
INdadt1 with INt1@0 MIN2@0 MIN3@0;
ODdadt3 with ODt3@0 MOD2@0 MOD3@0;
AIdadt4 with AIt4@0 MAI2@0 MAI3@0;

!M4 Analysis
INt1 (e);
AIt4 on HIt1 (c);
AIt4 on ODt3 (b);
ODt3 on HIt1 (a1);
ODt3 on INt1 (a2);

Output:     sampstat stdyx;
```

**Mplus Syntax for Figure 3.6**

```
Title:      M4 Model with bias-corrected bootstrap for HI,
            IN, OD, AI

Data:       file is T1T3T4 Kaylee moms dads.dat;

Define:     ! reverse key the four academic items moms
            rM1_AS1 = 6 - M1_AS1; rM1_AS2 = 6 - M1_AS2;
            rM1_AS3 = 6 - M1_AS3; rM1_AS4 = 6 - M1_AS4;
            rM3_AS1 = 6 - M3_AS1; rM3_AS2 = 6 - M3_AS2;
            rM3_AS3 = 6 - M3_AS3; rM3_AS4 = 6 - M3_AS4;
            rM4_AS1 = 6 - M4_AS1; rM4_AS2 = 6 - M4_AS2;
            rM4_AS3 = 6 - M4_AS3; rM4_AS4 = 6 - M4_AS4;

            ! create the three indicators for AI moms
            AI1momt1= mean (rM1_AS1 rM1_AS2);
            AI2momt1= (rM1_AS3); AI3momt1= (rM1_AS4);
            AI1momt3= mean (rM3_AS1 rM3_AS2);
```

```
AI2momt3= (rM3_AS3); AI3momt3= (rM3_AS4);
AI1momt4= mean (rM4_AS1 rM4_AS2);
AI2momt4= (rM4_AS3); AI3momt4= (rM4_AS4);

! reverse key codes for academic items dads
rF1_AS1 = 6 - F1_AS1; rF1_AS2 = 6 - F1_AS2;
rF1_AS3 = 6 - F1_AS3; rF1_AS4 = 6 - F1_AS4;
rF3_AS1 = 6 - F3_AS1; rF3_AS2 = 6 - F3_AS2;
rF3_AS3 = 6 - F3_AS3; rF3_AS4 = 6 - F3_AS4;
rF4_AS1 = 6 - F4_AS1; rF4_AS2 = 6 - F4_AS2;
rF4_AS3 = 6 - F4_AS3; rF4_AS4 = 6 - F4_AS4;

! create the three indicators for AI dads
AI1dadt1= mean (rF1_AS1 rF1_AS2);
AI2dadt1= (rF1_AS3); AI3dadt1= (rF1_AS4);
AI1dadt3= mean (rF3_AS1 rF3_AS2);
AI2dadt3= (rF3_AS3); AI3dadt3= (rF3_AS4);
AI1dadt4= mean (rF4_AS1 rF4_AS2);
AI2dadt4= (rF4_AS3); AI3dadt4= (rF4_AS4);

Variable:  Names are code schools sex classrm M1_AS1
           M1_AS2 M1_AS3 M1_AS4 M1_SC1 M1_SC2 M1_SC3
           M1_SC4 M1_SC5 M1_SC6 M1_SC7 M1_SC8 F1_AS1
           F1_AS2 F1_AS3 F1_AS4 F1_SC1 F1_SC2 F1_SC3
           F1_SC4 F1_SC5 F1_SC6 F1_SC7 F1_SC8 M3_AS1
           M3_AS2 M3_AS3 M3_AS4 M3_SC1 M3_SC2 M3_SC3
           M3_SC4 M3_SC5 M3_SC6 M3_SC7 M3_SC8 F3_AS1
           F3_AS2 F3_AS3 F3_AS4 F3_SC1 F3_SC2 F3_SC3
           F3_SC4 F3_SC5 F3_SC6 F3_SC7 F3_SC8 F4_SC1
           F4_SC2 F4_SC3 F4_SC4 F4_AS1 F4_AS2 F4_AS3
           F4_AS4 M4_SC1 M4_SC2 M4_SC3 M4_SC4 M4_AS1
           M4_AS2 M4_AS3 M4_AS4 IN1momT1 IN2momT1 IN3momT1
           HI1momT1 HI2momT1 HI3momT1 OD1momT1 OD2momT1
           OD3momT1 IN1dadT1 IN2dadT1 IN3dadT1 HI1dadT1
           HI2dadT1 HI3dadT1 OD1dadT1 OD2dadT1 OD3dadT1
           IN1momT3 IN2momT3 IN3momT3 HI1momT3 HI2momT3
           HI3momT3 OD1momT3 OD2momT3 OD3momT3 IN1dadT3
           IN2dadT3 IN3dadT3 HI1dadT3 HI2dadT3 HI3dadT3
           OD1dadT3 OD2dadT3 OD3dadT3 IN1momT4 IN2momT4
           IN3momT4 HI1momT4 HI2momT4 HI3momT4 OD1momT4
           OD2momT4 OD3momT4 IN1dadT4 IN2dadT4 IN3dadT4
           HI1dadT4 HI2dadT4 HI3dadT4 OD1dadT4 OD2dadT4
           OD3dadT4MT1_CE1 MT1_CE2 MT1_CE3 MT1_CE4 FT1_CE1
           FT1_CE2 FT1_CE3 FT1_CE4 MT3_CE1 MT3_CE2 MT3_CE3
           MT3_CE4 FT3_CE1 FT3_CE2 FT3_CE3 FT3_CE4 FT4_CE1
```

```
              FT4_CE2 FT4_CE3 FT4_CE4 MT4_CE1 MT4_CE2 MT4_CE3
              MT4_CE4;

              Missing are . ;

              Usevariables are HI1momT1 HI1dadT1 HI2momT1
              HI2dadT1 HI3momT1 HI3dadT1 IN1momT1 IN1dadT1
              IN2momT1 IN2dadT1 IN3momT1 IN3dadT1 OD1momT3
              OD1dadT3 OD2momT3 OD2dadT3 OD3momT3 OD3dadT3
              AI1momT4 AI1dadT4 AI2momT4 AI2dadT4 AI3momT4
              AI3dadT4;

Analysis:     type = RANDOM;
              algorithm = INTEGRATION;
              estimator = ML;

Model:        !HI factor structure
              HI1t1 by HI1momT1 HI1dadT1;
              HI2t1 by HI2momT1 HI2dadT1;
              HI3t1 by HI3momT1 HI3dadT1;
                   !latent means approach
              HIt1 by HI1t1@1 HI2t1@1 HI3t1@1;
              MHI2 by HI1t1@-1 HI2t1@1;
              MHI3 by HI1t1@-1 HI3t1@1;
                   !no first-order residual variance allowed
              HI1t1@0 HI2t1@0 HI3t1@0;

              HIdadt1 by HI1dadT1 HI2dadT1 HI3dadT1;

              HIdadt1 with HI1t1@0 HI2t1@0 HI3t1@0;

              !IN factor structure
              IN1t1 by IN1momT1 IN1dadT1;
              IN2t1 by IN2momT1 IN2dadT1;
              IN3t1 by IN3momT1 IN3dadT1;
                   !latent means approach
              INt1 by IN1t1@1 IN2t1@1 IN3t1@1;
              MIN2 by IN1t1@-1 IN2t1@1;
              MIN3 by IN1t1@-1 IN3t1@1;
                   !no first-order residual variance allowed
              IN1t1@0 IN2t1@0 IN3t1@0;

              INdadt1 by IN1dadT1 IN2dadT1 IN3dadT1;

              INdadt1 with IN1t1@0 IN2t1@0 IN3t1@0;
```

```
!OD factor structure
OD1t3 by OD1momT3 OD1dadT3;
OD2t3 by OD2momT3 OD2dadT3;
OD3t3 by OD3momT3 OD3dadT3;
     !latent means approach
ODt3 by OD1T3@1 OD2T3@1 OD3T3@1;
MOD2 by OD1T3@-1 OD2T3@1;
MOD3 by OD1T3@-1 OD3T3@1;
     !no first-order residual variance allowed
OD1t3@0 OD2t3@0 OD3t3@0;

ODdadt3 by OD1dadT3 OD2dadT3 OD3dadT3;

ODdadt3 with OD1t3@0 OD2t3@0 OD3t3@0;

!AI factor structure
AI1t4 by AI1momT4 AI1dadT4;
AI2t4 by AI2momT4 AI2dadT4;
AI3t4 by AI3momT4 AI3dadT4;
     !latent means approach
AIt4 by AI1T4@1 AI2T4@1 AI3T4@1;
MAI2 by AI1T4@-1 AI2T4@1;
MAI3 by AI1T4@-1 AI3T4@1;
     !no first-order residual variance allowed
AI1t4@0 AI2t4@0 AI3t4@0;

AIdadt4 by AI1dadT4 AI2dadT4 AI3dadT4;

AIdadt4 with AI1t4@0 AI2t4@0 AI3t4@0;

!Unrestricting correlations
HIt1 INt1 ODt3 AIt4 with MHI2 MHI3 MIN2 MIN3
MOD2 MOD3 MAI2 MAI3;
HIt1 with INdadt1 ODdadt3 AIdadt4;
INt1 with HIdadt1 ODdadt3 AIdadt4;
ODt3 with HIdadt1 INdadt1 AIdadt4;
AIt4 with HIdadt1 INdadt1 ODdadt3;

!Restricting correlations
HIdadt1 with HIt1@0 MHI2@0 MHI3@0;
INdadt1 with INt1@0 MIN2@0 MIN3@0;
ODdadt3 with ODt3@0 MOD2@0 MOD3@0;
AIdadt4 with AIt4@0 MAI2@0 MAI3@0;
```

```
            !M4 Analysis
            INt1 (e);
            AIt4 on HIt1 (c);
            AIt4 on ODt3 (b);
            ODt3 on HIt1 (a1);
            ODt3 on INt1 (a2);
            HIxINt1 | HIt1 xwith INt1;
            ODt3 on HIxINt1 (a3);

            Model constraint:
            NEW(INDEXMM P2SDW P1SDW MEANW N1SDW N2SDW);
            INDEXMM = a3*b;
            P2SDW = (a1 + a3*2*SQRT(e)) * b;
            P1SDW = (a1 + a3*1*SQRT(e)) * b;
            MEANW = (a1 + a3*0*SQRT(e)) * b;
            N1SDW = (a1 - a3*1*SQRT(e)) * b;
            N2SDW = (a1 - a3*2*SQRT(e)) * b;

Analysis:   bootstrap = 1000;
Output:     cinterval(bcbootstrap);
```

**Appendix C: References and Article ID for Meta-Analytic Review Articles**


2 You, J., Lin, M., & Leung, F. (2015). A longitudinal moderated mediation model of nonsuicidal self-injury among adolescents. *Journal of Abnormal Child Psychology*, *43*(2), 381-390. doi:10.1007/s10802-014-9901-x

4 Garn, A. C., Centeio, E., Shen, B., Martin, J., & McCaughtry, N. (2016). A moderated mediation analysis of children's physical activity enjoyment. *The Journal of Positive Psychology*, *11*(4), 428-438. doi:10.1080/17439760.2015.1092568

17 Bunford, N., Evans, S. W., Becker, S. P., & Langberg, J. M. (2015). Attention-deficit/hyperactivity disorder and social skills in youth: A moderated mediation model of emotion dysregulation and depression. *Journal of Abnormal Child Psychology*, *43*(2), 283-296. doi:10.1007/s10802-014-9909-2

19 Felleman, B. I., Athenour, D. R., Ta, M. T., & Stewart, D. G. (2013). Behavioral health services influence medical treatment utilization among primary care patients with comorbid substance use and depression. *Journal of Clinical Psychology in Medical Settings*, *20*(4), 415-426. doi:10.1007/s10880-013-9367-y

21 Baardstu, S., Karevold, E. B., & von Soest, T. (2017). Childhood antecedents of Agreeableness: A longitudinal study from preschool to late adolescence. *Journal of Research In Personality*, *67*202-214. doi:10.1016/j.jrp.2016.10.007

25 Lamis, D. A., Ballard, E. D., May, A. M., & Dvorak, R. D. (2016). Depressive symptoms and suicidal ideation in college students: The mediating and

moderating roles of hopelessness, alcohol problems, and social support. *Journal of Clinical Psychology*, *72*(9), 919-932. doi:10.1002/jclp.22295

26 Schacter, H. L., & Juvonen, J. (2017). Depressive symptoms, friend distress, and self-blame: Risk factors for adolescent peer victimization. *Journal of Applied Developmental Psychology*, *51*35-43. doi:10.1016/j.appdev.2017.02.005

36 Brothers, A., Miche, M., Wahl, H., & Diehl, M. (2017). Examination of associations among three distinct subjective aging constructs and their relevance for predicting developmental correlates. *The Journals of Gerontology: Series B: Psychological Sciences and Social Sciences*, *72*(4), 547-560.

37 Norcross, P. L., Leerkes, E. M., & Zhou, N. (2017). Examining pathways linking maternal depressive symptoms in infancy to children's behavior problems: The role of maternal unresponsiveness and negative behaviors. *Infant Behavior & Development*, *49*238-247. doi:10.1016/j.infbeh.2017.09.009

46 van Beusekom, G., Baams, L., Bos, H. W., Overbeek, G., & Sandfort, T. M. (2016). Gender nonconformity, homophobic peer victimization, and mental health: How same-sex attraction and biological sex matter. *Journal of Sex Research*, *53*(1), 98-108. doi:10.1080/00224499.2014.993462

47 Starr, L. R., & Hammen, C. (2016). Genetic moderation of the association between adolescent romantic involvement and depression: Contributions of serotonin transporter gene polymorphism, chronic stress, and family discord. *Development and Psychopathology*, *28*(2), 447-457. doi:10.1017/S0954579415000498

49 Meule, A., Hofmann, J., Weghuber, D., & Blechert, J. (2016). Impulsivity, perceived self-regulatory success in dieting, and body mass in children and adolescents: A moderated mediation model. *Appetite*, *107*15-20. doi:10.1016/j.appet.2016.07.022

50 Racine, S. E., & Martin, S. J. (2017). Integrating eating disorder-specific risk factors into the acquired preparedness model of dysregulated eating: A moderated mediation analysis. *Eating Behaviors*, *24*54-60. doi:10.1016/j.eatbeh.2016.12.007

53 Hamilton, J. L., Connolly, S. L., Liu, R. T., Stange, J. P., Abramson, L. Y., & Alloy, L. B. (2015). It gets better: Future orientation buffers the development of hopelessness and depressive symptoms following emotional victimization during early adolescence. *Journal of Abnormal Child Psychology*, *43*(3), 465-474. doi:10.1007/s10802-014-9913-6

55 Zhu, H., Luo, X., Cai, T., He, J., Lu, Y., & Wu, S. (2016). Life event stress and binge eating among adolescents: The roles of early maladaptive schemas and impulsivity. *Stress and Health: Journal of The International Society For The Investigation of Stress*, *32*(4), 395-401. doi:10.1002/smi.2634

56 Brock, R. L., Kochanska, G., O'Hara, M. W., & Grekin, R. S. (2015). Life satisfaction moderates the effectiveness of a play-based parenting intervention in low-income mothers and toddlers. *Journal of Abnormal Child Psychology*, *43*(7), 1283-1294. doi:10.1007/s10802-015-0014-y

58 Haugh, J. A., Miceli, M., & DeLorme, J. (2017). Maladaptive parenting, temperament, early maladaptive schemas, and depression: A moderated mediation

analysis. *Journal of Psychopathology and Behavioral Assessment*, *39*(1), 103-116. doi:10.1007/s10862-016-9559-5

59 Hummel, A. C., & Kiel, E. J. (2015). Maternal depressive symptoms, maternal behavior, and toddler internalizing outcomes: A moderated mediation model. *Child Psychiatry and Human Development*, *46*(1), 21-33. doi:10.1007/s10578-014-0448-4

63 Tsafou, K., De Ridder, D. D., van Ee, R., & Lacroix, J. W. (2016). Mindfulness and satisfaction in physical activity: A cross-sectional study in the Dutch population. *Journal of Health Psychology*, *21*(9), 1817-1827. doi:10.1177/1359105314567207

68 Kim, S., & Kochanska, G. (2015). Mothers' power assertion; children's negative, adversarial orientation; and future behavior problems in low-income families: Early maternal responsiveness as a moderator of the developmental cascade. *Journal of Family Psychology*, *29*(1), 1-9. doi:10.1037/a0038430

69 Brewster, M. E., Moradi, B., DeBlaere, C., & Velez, B. L. (2013). Navigating the borderlands: The roles of minority stressors, bicultural self-efficacy, and cognitive flexibility in the mental health of bisexual individuals. *Journal of Counseling Psychology*, *60*(4), 543-556. doi:10.1037/a0033224

70 Murphy, S., Murphy, J., & Shevlin, M. (2015). Negative evaluations of self and others, and peer victimization as mediators of the relationship between childhood adversity and psychotic experiences in adolescence: The moderating role of loneliness. *British Journal of Clinical Psychology*, *54*(3), 326-344. doi:10.1111/bjc.12077

73 Jin, Z., Zhang, X., & Han, Z. R. (2017). Parental emotion socialization and child psychological adjustment among Chinese urban families: Mediation through child emotion regulation and moderation through dyadic collaboration. *Frontiers in Psychology*, *8,* doi:10.3389/fpsyg.2017.02198

75 Casalin, S., Tang, E., Vliegen, N., & Luyten, P. (2014). Parental personality, stress generation, and infant temperament in emergent parent-child relationships: Evidence for a moderated mediation model. *Journal of Social and Clinical Psychology*, *33*(3), 270-291. doi:10.1521/jscp.2014.33.3.270

86 Perrino, T., Pantin, H., Prado, G., Huang, S., Brincks, A., Howe, G., & ... Brown, C. H. (2014). Preventing internalizing symptoms among Hispanic adolescents: A synthesis across Familias Unidas trials. *Prevention Science*, *15*(6), 917-928. doi:10.1007/s11121-013-0448-9

94 Thomas, K. K., & Bowker, J. C. (2015). Rejection sensitivity and adjustment during adolescence: Do friendship self-silencing and parent support matter? *Journal of Child and Family Studies*, *24*(3), 608-616. doi:10.1007/s10826-013-9871-6

99 Talaei-Khoei, M., Chen, N., Ring, D., & Vranceanu, A. (2018). Satisfaction with life moderates the indirect effect of pain intensity on pain interference through pain catastrophizing. *Journal of Consulting and Clinical Psychology*, *86*(3), 231-241. doi:10.1037/ccp0000283

100 Li, D., Li, X., Wang, Y., Zhao, L., Bao, Z., & Wen, F. (2013). School connectedness and problematic Internet use in adolescents: A moderated

mediation model of deviant peer affiliation and self-control. *Journal of Abnormal Child Psychology*, *41*(8), 1231-1242. doi:10.1007/s10802-013-9761-9

111 Chen, W., Niu, G., Zhang, D., Fan, C., Tian, Y., & Zhou, Z. (2016). Socioeconomic status and life satisfaction in Chinese adolescents: Analysis of self-esteem as a mediator and optimism as a moderator. *Personality and Individual Differences*, *95*105-109. doi:10.1016/j.paid.2016.01.036

124 Mallette, J. K., Futris, T. G., Brown, G. L., & Oshri, A. (2015). The influence of father involvement and interparental relationship quality on adolescent mothers' maternal identity. *Family Relations: An Interdisciplinary Journal of Applied Family Studies*, *64*(4), 476-489. doi:10.1111/fare.12132

127 Chow, P. I., & Berenbaum, H. (2016). The relation between depression and appreciation: The role of perceptions of emotional utility in an experimental test of causality. *Cognition and Emotion*, *30*(4), 797-806. doi:10.1080/02699931.2015.1022511

129 Vieselmeyer, J., Holguin, J., & Mezulis, A. (2017). The role of resilience and gratitude in posttraumatic stress and growth following a campus shooting. *Psychological Trauma: Theory, Research, Practice, And Policy*, *9*(1), 62-69. doi:10.1037/tra0000149

130 Hamilton, K., Warner, L. M., & Schwarzer, R. (2017). The role of self-efficacy and friend support on adolescent vigorous physical activity. *Health Education & Behavior*, *44*(1), 175-181. doi:10.1177/1090198116648266

## Appendix D: Results from Meta-Analytic Literature Review

| ID | *X* variable | *M* variable | *Y* variable | *W* variable | *N* | *miss* | $a_1$ | $a_2$ | $a_3$ | $b$ | $c'$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Bipolar disorder | Negative emotions | Nonsuicidal self injury | Behavioral impulsivity | 2994 | .34 | **.26** | -9 | **.28** | **.06** | -9 |
| 2 | Bipolar disorder | Negative emotions | Nonsuicidal self injury | Self-criticism | 2990 | .34 | **.26** | -9 | .00 | **.06** | -9 |
| 4 | Social support from friends | Ability beliefs about physical activity | Physical activity enjoyment | Support seeking self efficacy | 327 | .04 | **.12** | **.38** | **.12** | **.22** | **.11** |
| 4 | Social support from friends | Subjective task value toward physical activity | Physical activity enjoyment | Support seeking self efficacy | 327 | .04 | .06 | **.32** | .02 | **.12** | **.11** |
| 17 | Adhd | Self-awareness | Social skills impairment | Depression | 171 | .05 | **.26** | .02 | **.23** | **.17** | **.25** |
| 17 | Adhd | Emotional control | Social skills impairment | Depression | 171 | .05 | **.15** | .07 | .08 | .14 | **.19** |
| 19 | Substance use disorder | Behavioral health services | Medical treatment utilization | Depression | 224 | -9 | .06 | **-.68** | **-.07** | **.57** | **.46** |
| 21 | Difficultness (age 4.5) | Reactivity (age 12.5) | Agreeableness (age 16.5) | Parental reasoning (age 8.5) | 965 | .11 | **.19** | -.04 | .01 | **-.30** | -.08 |
| 21 | Difficultness (age 4.5) | Reactivity (age 12.5) | Agreeableness (age 16.5) | Parental warmth (age 8.5) | 965 | .11 | **.20** | -.01 | .07 | **-.22** | -.07 |
| 21 | Difficultness (age 4.5) | Reactivity (age 12.5) | Agreeableness (age 16.5) | Parental punishment (age 8.5) | 965 | .11 | **.18** | .05 | .09 | **-.23** | -.11 |
| 25 | Depression | Hopelessness | Likelihood of experiencing suicide ideation | Social support | 2034 | -9 | **.45** | **-.19** | **-.20** | **.20** | **.34** |
| 25 | Depression | Hopelessness | Severity of suicidal ideation | Social support | 2034 | -9 | **.45** | **-.19** | **-.20** | **.21** | **.33** |
| 26 | Depressive symptoms | Characterological self-blame | Victimization | Friend depressive symptoms | 5374 | -9 | **.10** | .01 | **.03** | **.19** | **.08** |
| 36 | Felt age | Awareness of age-related change (aarc) gains | Physical functioning | Age | 819 | -9 | .04 | .05 | .05 | .07 | .03 |
| 36 | Felt age | AARC gains | Life satisfaction | Age | 819 | -9 | .04 | .05 | .05 | .07 | .05 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 36 | Atoa | Aarc gains | Physical functioning | Age | 819 | -9 | .07 | **.10** | .04 | **.07** | .02 |
| 36 | Atoa | Aarc gains | Life satisfaction | Age | 819 | -9 | .07 | **.10** | .04 | .04 | **.11** |
| 36 | Felt age | Aarc losses | Physical functioning | Age | 819 | -9 | **.10** | **.15** | .05 | .01 | .00 |
| 36 | Felt age | Aarc losses | Life satisfaction | Age | 819 | -9 | **.10** | **.15** | .05 | **.14** | .05 |
| 36 | Atoa | Aarc losses | Physical functioning | Age | 819 | -9 | **.15** | .06 | .04 | .04 | .02 |
| 36 | Atoa | Aarc losses | Life satisfaction | Age | 819 | -9 | **.16** | .05 | .05 | .07 | **.11** |
| 37 | Maternal depression (prenatal & 6 month avg) | Unresponsive behaviors (6 months) | Internalizing behaviors (2 years) | Observed infant affect | 259 | -9 | **.34** | -9 | **.16** | .10 | **.24** |
| 37 | Maternal depression (prenatal & 6 month avg) | Unresponsive behaviors (6 months) | Externalizing behaviors (2 years) | Observed infant affect | 259 | -9 | **.34** | -9 | **.16** | .13 | .13 |
| 46 | Gender noncomformity | Homophobic name-calling | Social anxiety | Sexual attraction | 1,026 | -9 | **.11** | **.11** | **.06** | **.07** | **.28** |
| 46 | Gender noncomformity | Homophobic name-calling | Psychological distress | Sexual attraction | 1,026 | -9 | **.11** | **.11** | **.06** | **.19** | **.26** |
| 47 | Age 15 romantic relationship | Age 20 chronic stress | Age 20 depressive symptoms | 5-httlpr (genetics) | 815 | .13 | .05 | .05 | **.08** | **.15** | .04 |
| 49 | Attentional impulsivity | Perceived self-regulatory success in dieting | Body mass index percentile | Motor impulsivity | 122 | -9 | .15 | .05 | **.22** | **.29** | .03 |
| 49 | Attentional impulsivity | Perceived self-regulatory success in dieting | Body mass index percentile | Non-planning impulsivity | 122 | -9 | .15 | **.22** | .02 | **.29** | .03 |
| 50 | Negative urgency | Eating expectancies | Dysregulated eating | Appearance pressures | 313 | -9 | **.36** | **.24** | .06 | **.22** | **.36** |
| 50 | Negative urgency | Eating expectancies | Dysregulated eating | Thin-ideal internalization | 313 | -9 | **.36** | **.02** | .11 | **.37** | **.37** |
| 50 | Negative urgency | Eating expectancies | Dysregulated eating | Body dissatisfaction | 313 | -9 | **.37** | .06 | .01 | **.42** | **.33** |
| 50 | Negative urgency | Eating expectancies | Dysregulated eating | Dietary restraint | 313 | -9 | **.38** | .10 | .02 | **.41** | **.40** |
| 53 | Peer emotional victimization | Hopelessness | Depressive symptoms | Future orientation | 259 | -9 | **.20** | .01 | **.19** | **.21** | **.23** |
| 53 | Familial emotional victimization | Hopelessness | Depressive symptoms | Future orientation | 259 | -9 | **.21** | .10 | **.16** | **.19** | **.27** |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 55 | Life event stress | Early maladaptive schemas | Binge eating | Impulsivity | 2359 | .08 | **.42** | **.21** | **.06** | **.18** | **.09** |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Commited compliance | Mothers self-report life satisfaction | 186 | .13 | -.08 | .19 | **-.26** | **-.25** | -9 |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Opposition | Mothers self-report life satisfaction | 186 | .13 | -.08 | .19 | **-.26** | **.26** | -9 |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Externalizing behaviors | Mothers self-report life satisfaction | 186 | .13 | -.08 | .19 | **-.26** | **.16** | -9 |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Internalizing behaviors | Mothers self-report life satisfaction | 186 | .13 | -.08 | .19 | **-.26** | .10 | -9 |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Commited compliance | Clinician rated maternal psychosocial functioning | 186 | .13 | -.07 | .00 | -.04 | **-.27** | -9 |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Opposition | Clinician rated maternal psychosocial functioning | 186 | .13 | -.07 | .00 | -.04 | **.28** | -9 |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Externalizing behaviors | Clinician rated maternal psychosocial functioning | 186 | .13 | -.07 | .00 | -.04 | **.15** | -9 |
| 56 | Play group vs play as usual | Mothers power assertive discipline | Internalizing behaviors | Clinician rated maternal psychosocial functioning | 186 | .13 | -.07 | .00 | -.04 | .07 | -9 |
| 58 | Emotionally depriving | Disconnection/ rejection | Depressive symptoms | Negative affect | 403 | -9 | .04 | **.22** | .02 | **.64** | .03 |
| 58 | Emotionally depriving | Disconnection/ rejection | Depressive symptoms | Extraversion | 403 | -9 | .05 | **.15** | .01 | **.64** | .03 |
| 58 | Emotionally depriving | Impaired autonomy & performance | Depressive symptoms | Negative affect | 403 | -9 | .01 | **.23** | .05 | **.66** | .05 |
| 58 | Emotionally depriving | Impaired autonomy & performance | Depressive symptoms | Extraversion | 403 | -9 | .00 | **.14** | .04 | **.66** | .05 |
| 58 | Over-protective | Disconnection/ rejection | Depressive symptoms | Negative affect | 403 | -9 | .03 | **.14** | .08 | **.64** | .02 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 58 | Over-protective | Disconnection/ rejection | Depressive symptoms | Extraversion | 403 | -9 | .05 | **.15** | .01 | **.64** | .02 |
| 58 | Over-protective | Impaired autonomy & performance | Depressive symptoms | Negative affect | 403 | -9 | .06 | **.14** | **.11** | **.67** | .04 |
| 58 | Over-protective | Impaired autonomy & performance | Depressive symptoms | Extraversion | 403 | -9 | .02 | .09 | .02 | **.67** | .04 |
| 58 | Belittling | Disconnection/ rejection | Depressive symptoms | Negative affect | 403 | -9 | .03 | **.19** | .08 | **.63** | .04 |
| 58 | Belittling | Disconnection/ rejection | Depressive symptoms | Extraversion | 403 | -9 | .08 | **.27** | **.12** | **.63** | .04 |
| 58 | Belittling | Impaired autonomy & performance | Depressive symptoms | Negative affect | 403 | -9 | .03 | **.24** | .08 | **.71** | .03 |
| 58 | Belittling | Impaired autonomy & performance | Depressive symptoms | Extraversion | 403 | -9 | **.12** | **.25** | **.16** | **.71** | .03 |
| 59 | Maternal depressive symptoms | Warmth | Toddler internalizing outcomes | Toddler negative emotionality | 91 | .23 | .09 | .15 | .05 | .04 | .12 |
| 63 | Mindfulness | Satisfaction | Physical activity | Activity habit | 398 | -9 | **.38** | **.16** | **-.09** | **.10** | .03 |
| 69 | Anti-bisexual prejudice | Expectations of stigma | Psychological distress | Bicultural self-efficacy (SE) | 411 | -9 | **.28** | **-.22** | .05 | .10 | **.11** |
| 69 | Anti-bisexual prejudice | Internalized biphobia | Psychological distress | Bicultural SE | 411 | -9 | .02 | **-.34** | .04 | .12 | **.11** |
| 69 | Anti-bisexual prejudice | Outness | Psychological distress | Bicultural SE | 411 | -9 | **.22** | **.15** | .06 | -.07 | **.11** |
| 69 | Anti-bisexual prejudice | Expectations of stigma | Psychological well-being | Bicultural SE | 411 | -9 | **.28** | **-.22** | .05 | **-.12** | -.03 |
| 69 | Anti-bisexual prejudice | Internalized biphobia | Psychological well-being | Bicultural SE | 411 | -9 | .02 | **-.36** | .04 | **-.20** | -.03 |
| 69 | Anti-bisexual prejudice | Outness | Psychological well-being | Bicultural SE | 411 | -9 | **.22** | **.15** | .06 | .08 | -.03 |
| 69 | Anti-bisexual prejudice | Expectations of stigma | Psychological distress | Cognitive flexibility | 411 | -9 | **.31** | **-.17** | **.14** | .04 | **.12** |
| 69 | Anti-bisexual prejudice | Internalized biphobia | Psychological distress | Cognitive flexibility | 411 | -9 | .08 | **-.23** | .01 | .05 | **.12** |
| 69 | Anti-bisexual prejudice | Outness | Psychological distress | Cognitive flexibility | 411 | -9 | **.22** | **.15** | .06 | -.01 | **.12** |
| 69 | Anti-bisexual prejudice | Expectations of stigma | Psychological well-being | Cognitive flexibility | 411 | -9 | **.31** | **-.17** | **.14** | **-.11** | **-.08** |
| 69 | Anti-bisexual prejudice | Internalized biphobia | Psychological well-being | Cognitive flexibility | 411 | -9 | .08 | **-.23** | .01 | **-.13** | **-.08** |
| 69 | Anti-bisexual prejudice | Outness | Psychological well-being | Cognitive flexibility | 411 | -9 | **.22** | **.15** | .06 | .03 | **-.08** |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 70 | Early life experiences | Social comparison | Psychotic experiences | Loneliness | 785 | .00 | **.17** | .05 | .01 | .06 | **.10** |
| 70 | Early life experiences | Post-traumatic cognitions | Psychotic experiences | Loneliness | 785 | .00 | **.46** | **.08** | **.16** | **.16** | **.10** |
| 70 | Early life experiences | Peer victimisation | Psychotic experiences | Loneliness | 785 | .00 | **.24** | .04 | .05 | **.14** | **.10** |
| 73 | Supportive reactions to child's negative emotions | Child emotion regulation | Internalizing symptoms | Parent/child dyadic collaboration | 150 | -9 | **.39** | -9 | **.21** | **-.34** | -.15 |
| 73 | Supportive reactions to child's negative emotions | Child emotion regulation | Externalizing symptoms | Parent/child dyadic collaboration | 150 | -9 | **.39** | -9 | **.21** | **-.35** | -.10 |
| 73 | Unsupportive reactions to child's negative emotions | Child emotion regulation | Internalizing symptoms | Parent/child dyadic collaboration | 150 | -9 | **-.20** | -9 | -.08 | **-.36** | .14 |
| 73 | Unsupportive reactions to child's negative emotions | Child emotion regulation | Externalizing symptoms | Parent/child dyadic collaboration | 150 | -9 | **-.20** | -9 | -.08 | **-.38** | .04 |
| 86 | Intervention condition | Post-intervention communication | Trajectory of internalizing | Baseline communication | 721 | -9 | **.16** | .03 | **.14** | **.12** | **.07** |
| 94 | Rejection sensitivity | Friendship self-silencing | Friendship support | Parental support | 103 | -9 | **.26** | -9 | **.24** | **.25** | .10 |
| 94 | Rejection sensitivity | Friendship self-silencing | Depression | Parental support | 103 | -9 | **.24** | -9 | **.24** | **.25** | .17 |
| 99 | Pain intensity | Pain catastrophizing | Pain interference | Satisfaction with life | 142 | -9 | **.31** | **.34** | **.21** | **.39** | **.38** |
| 100 | School connectedness | Affiliation with deviant peers | Problematic internet use | Self-control | 2758 | .02 | -.21 | -.09 | .07 | .18 | -.03 |
| 111 | SES | Adolescent's self esteem | Life satisfaction | Optimism | 688 | -9 | **-.20** | **.68** | **.08** | **.18** | -.07 |
| 124 | Prenatal father involvement | Post-birth father child involvement | Maternal identity | Interparental relationship quality | 125 | -9 | **.61** | **.32** | **.09** | .14 | **.31** |
| 129 | Trauma exposure | Post-traumatic stress | Posttraumatic growth | Resilience | 359 | -9 | **.16** | -9 | **.10** | .05 | **.21** |
| 130 | Self-efficacy | Intention | Vigorous physical activity (1 week later) | Friend support | 226 | -9 | **.70** | **.14** | **-.10** | **.27** | -.07 |

*Note*. Bold values indicate estimates that were statistically significant. $N$ = the sample size, *miss* = proportion of missing in analysis.

## Appendix E: Standardizing M and Y Trait Factors

Standardizing *X*, *W*, *M*, and *Y* constructs in order to calculate factor loading estimates to determine the relative proportion of method variance with each construct. Known values used in calculations are included in the table below. Note that all *X*, *M*, *W*, and *Y* latent means were set to 0.

| Parameter Label | Parameter Value |
|---|---|
| $Var(\varepsilon_{imt})$ | .2 |
| $Var(T_{imX})$ | 1.0 |
| $Var(T_{imW})$ | 1.0 |
| $Var(T_{imM})$ | 1.0 |
| $Var(T_{imY})$ | 1.0 |
| $Var(M_{imt})$ | 1.0 |
| $Corr(T_{1mX}, T_{1mW})$ | .5 |
| $a_1$ | .275 |
| $a_2$ | .255 |
| $a_3$ | .147 |
| $b$ | .235 |
| $c'$ | .195 |

Models were standardized by setting variances for *X*, *W*, *M*, and *Y* to 1.0. To standardize the *M* and *Y* factors in M*plus*, residual variances for *M* and *Y* were calculated and appropriate model constraints were implemented. Covariance algebra was used following MacKinnon (2008) and Appendix A in Thoemmes, MacKinnon, & Reiser (2010).

### Standardizing *M*

The variance of the trait, *M*, is dependent on the variance of the trait, *X*, the variance of the trait, *W*, the covariance between *X* and *W*, and a residual term.

$$Var(T_{1mM}) = a_1^2 Var(T_{1mX}) + a_2^2 Var(T_{1mW}) + 2a_1 a_2 Cov(T_{1mX}, T_{1mW}) + Var(e_M)$$

Substituting 1 for all factor variances resulted in a simplified equation shown below.

$$1 = a_1^2 \times 1 + a_2^2 \times 1 + 2a_1 a_2 Cov(T_{1mX}, T_{1mW}) + Var(e_M)$$

$$1 = a_1^2 + a_2^2 + 2a_1 a_2 Cov(T_{1mX}, T_{1mW}) + Var(e_M)$$

Algebra was used to solve for the residual factor variance of the *M* trait factor, and values were substituted to find the residual variance for *M*.

$$\begin{aligned} Var(e_M) &= 1 - a_1^2 - a_2^2 - 2a_1 a_2 Cov(T_{1mX}, T_{1mW}) \\ &= 1 - (.275)^2 - (.255)^2 - 2(.275)(.255)(.5) \\ &= .7892 \end{aligned}$$

The residual variance for *M*, given other known values, was $Var(e_M) = .7892$.

**Standardizing *Y***

The variance of the trait, *Y*, is dependent on the variance of *X*, the variance of *M*, the covariance between *X* and *M* (which is the product of the $a_1$ path and the variance of *X*, MacKinnon, 2008, p. 86), and a residual term.

$$Var(T_{1mY}) = b^2 Var(T_{1mM}) + c'^2 Var(T_{1mX}) + 2bc' Cov(T_{1mM}, T_{1mX}) + Var(e_Y)$$

The variance of the trait, *M*, is dependent on the variance of *X*, the variance of *W*, the covariance between *X* and *W*, and a residual term, as shown in the section above. Substituting the equation for the variance of *M* results in the following full equation.

$$\begin{aligned} Var(T_{1mY}) = b^2 &\left[ a_1^2 Var(T_{1mX}) + a_2^2 Var(T_{1mW}) + 2a_1 a_2 Cov(T_{1mX}, T_{1mW}) + Var(e_M) \right] \\ &+ c'^2 Var(T_{1mX}) + 2bc' \left[ a_1 Var(T_{1mX}) \right] + Var(e_Y) \end{aligned}$$

Substituting 1 for all factor variances resulted in a simplified equation as shown below.

$$1 = b^2 \left[ a_1^2 \times 1 + a_2^2 \times 1 + 2a_1 a_2 Cov(T_{1mX}, T_{1mW}) + Var(e_M) \right] + c'^2 \times 1 + 2a_1 bc' \times 1 + Var(e_Y)$$

$$1 = b^2 \left[ a_1^2 + a_2^2 + 2a_1 a_2 Cov(T_{1mX}, T_{1mW}) + Var(e_M) \right] + c'^2 + 2a_1 bc' + Var(e_Y)$$

Algebra was used to solve for the residual factor variance for the *M* trait factor.

$$Var(e_Y) = 1 - b^2\left[a_1^2 + a_2^2 + 2a_1a_2Cov(T_{1mX}, T_{1mW}) + Var(e_M)\right] - c'^2 - 2a_1bc'$$

It was also known that the variance of the *M* trait factor was equal to 1, meaning the equation could be even further reduced.

$$Var(e_Y) = 1 - b^2 \times 1 - c'^2 - 2a_1bc'$$

$$= 1 - b^2 - c'^2 - 2a_1bc'$$

Values were substituted to find the residual variance for *Y*.

$$\begin{aligned} Var(e_Y) &= 1 - (.235)^2 - (.195)^2 - 2(.275)(.235)(.195) \\ &= .8815 \end{aligned}$$

The residual variance for *Y*, given other known values, was $Var(e_Y) = .8815$

**Setting *M* and *Y* Factor Variances to 1 in Mplus**

In M*plus*, model constraints were used to ensure that the variances of *M* and *Y* were both set equal to 1. These constraints used the following code:

```
Model constraint:

0 = a1^2+a2^2+2*a1*a2*cov+varM - 1;
0 = b^2*(a1^2+a2^2+2*a1*a2*cov+varM)+c^2+2*a1*b*c+varY
- 1;
```

This piece of code corresponds to equations presented earlier in this appendix. The variances of *X* and *W* could easily be set to 1 without using model constraints.

**Appendix F: Determining λ and γ to accurately estimate $Con(\tau_{imt})$ & $Mspe(\tau_{imt})$**

All trait and method factors had a total variance equal to 1.0 or the total variance of the factor was calculated to be equal to 1.0. Therefore, estimating consistency and method-specificity was equal across *X*, *M*, *W*, and *Y* factors. To calculate consistency and method specificity, factor loadings were appropriately estimated.

*Reference Method Indicators*: For indicators pertaining to the reference method, a simple equation was used to calculate λ, solving from Equation 29 from Chapter III.

$$\lambda_{i1t} = \sqrt{\frac{Con(T_{1mt})\left[\gamma_{imt}^2 Var(M_{imt}) + Var(\varepsilon)\right]}{Var(T_{1mt}) - Con(T_{1mt})}}$$

Because the reference method does not load onto any method factor, γ implicitly equals 0 and was used to reduce the equation. Further, substituting 1 for all factor variances resulted in a simplified equation shown below.

$$\lambda_{i1t} = \sqrt{\frac{Con(T_{1mt})\left[0 \times Var(M_{imt}) + Var(\varepsilon)\right]}{1 - Con(T_{1mt})}}$$

$$= \sqrt{\frac{Con(T_{1mt}) \times Var(\varepsilon)}{1 - Con(T_{1mt})}}$$

*Non-reference Method Indicators*. For indicators pertaining to the non-reference method, the following system of linear equations was used to determine parameter estimates for λ and γ pertaining to *X* and *W*. The system of equations restructures the consistency and method-specificity equations from Chapter III, setting values equal to 0.

$$\begin{cases} 0 = Con(Y_{imt})\left[\lambda_{imt}^2 Var(T_{1mt}) + \gamma_{imt}^2 Var(M_{imt}) + Var(\varepsilon)\right] - \lambda_{imt}^2 Var(T_{1mt}) \\ 0 = Mspe(Y_{imt})\left[\lambda_{imt}^2 Var(T_{1mt}) + \gamma_{imt}^2 Var(M_{imt}) + Var(\varepsilon)\right] - \gamma_{imt}^2 Var(M_{imt}) \end{cases}$$

Substituting 1 for all factor variances resulted in a simplified system of equations.

$$\begin{cases} 0 = Con(Y_{imt})\left[\lambda_{imt}^2 \times 1 + \gamma_{imt}^2 \times 1 + Var(\varepsilon)\right] - \lambda_{imt}^2 \times 1 \\ 0 = Mspe(Y_{imt})\left[\lambda_{imt}^2 \times 1 + \gamma_{imt}^2 \times 1 + Var(\varepsilon)\right] - \gamma_{imt}^2 \times 1 \end{cases}$$

$$\begin{cases} 0 = Con(Y_{imt})\left[\lambda_{imt}^2 + \gamma_{imt}^2 + Var(\varepsilon)\right] - \lambda_{imt}^2 \\ 0 = Mspe(Y_{imt})\left[\lambda_{imt}^2 + \gamma_{imt}^2 + Var(\varepsilon)\right] - \gamma_{imt}^2 \end{cases}$$

Known parameter values for each condition were substituted into the system of equations, resulting in λ and γ for each of the simulation conditions.

## Appendix G: Example M*plus* Code for the Monte Carlo Simulation Study

### Example Code for Correct Model Specification

```
Title:        M4 Model

Montecarlo:   names are X1mom X2mom X3mom X1dad X2dad X3dad
                        M1mom M2mom M3mom M1dad M2dad M3dad
                        Y1mom Y2mom Y3mom Y1dad Y2dad Y3dad
                        W1mom W2mom W3mom W1dad W2dad
              W3dad;
              nobservations = 200; !sample size
              nreps = 500; !number of replications
              seed = 84780;

              MODEL POPULATION:
              XxW | X XWITH W; !create interaction term

              ! MTMM Model Con = .8, Mspe = .2
              X by X1mom*.894 X1dad*.8 X2mom*.894 X2dad*.8
              X3mom*.894 X3dad*.8;
              M by M1mom*.894 M1dad*.8 M2mom*.894 M2dad*.8
              M3mom*.894 M3dad*.8;
              Y by Y1mom*.894 Y1dad*.8 Y2mom*.894 Y2dad*.8
              Y3mom*.894 Y3dad*.8;
              W by W1mom*.894 W1dad*.8 W2mom*.894 W2dad*.8
              W3mom*.894 W3dad*.8;

              ! M-1 method factors
              Xdad by X1dad*.4 X2dad*.4 X3dad*.4;
              Mdad by M1dad*.4 M2dad*.4 M3dad*.4;
              Ydad by Y1dad*.4 Y2dad*.4 Y3dad*.4;
              Wdad by W1dad*.4 W2dad*.4 W3dad*.4;

              !Intercepts - values based on application
              [X1mom*1.02 X2mom*0.88 X3mom*1.02 X1dad*1.01
              X2dad*0.90 X3dad*1.02];
              [M1mom*1.03 M2mom*0.87 M3mom*0.99 M1dad*1.03
              M2dad*0.86 M3dad*0.97];
              [Y1mom*1.58 Y2mom*1.41 Y3mom*1.58 Y1dad*1.63
              Y2dad*1.40 Y3dad*1.62];
              [W1mom*0.98 W2mom*1.06 W3mom*1.04 W1dad*1.05
              W2dad*1.07 W3dad*1.05];
              [X@0 M@0 W@0 Y@0];
```

```
!Correlations not allowed
X with Xdad@0;
M with Mdad@0;
Y with Ydad@0;
W with Wdad@0;
!Corr between methods and common traits not
of same method - based on application
Xdad with M*.10 Y*.10 W*.08;
Mdad with X*.18 Y*.02 W*.13;
Ydad with X*.13 M*.03 W*.22;
Wdad with X*.04 M*.07 Y*.12;
!Correlation between X and W
X with W*0.5;

!Correlation between method factors
Xdad with Wdad*0.2 Mdad*0.2 Ydad*0.2;
Wdad with Mdad*0.2 Ydad*0.2;
Mdad with Ydad*0.2;

!Variances - standardized
X1mom*.2 X1dad*.2 X2mom*.2 X2dad*.2 X3mom*.2
X3dad*.2;
W1mom*.2 W1dad*.2 W2mom*.2 W2dad*.2 W3mom*.2
W3dad*.2;
M1mom*.2 M1dad*.2 M2mom*.2 M2dad*.2 M3mom*.2
M3dad*.2;
Y1mom*.2 Y1dad*.2 Y2mom*.2 Y2dad*.2 Y3mom*.2
Y3dad*.2;
X@1 Xdad@1;
W@1 Wdad@1;
M@.7892 Mdad@1;
Y@.8815 Ydad@1;

!Moderated mediation effects based on lit
review
M on X*0.275 (a1);
M on W*0.255 (a2);
M on XxW*0.147 (a3);
Y on M*0.235 (b);
Y on X*0.194 (c);

Analysis:     type = RANDOM;
              algorithm = INTEGRATION;
              estimator = ML;
```

```
Model:        XxW | X XWITH W; !create interaction term

              ! MTMM Model - Con = .8, Mspe = .2
              X by X1mom*.894
                   X1dad*.8 (x1d)
                   X2mom*.894
                   X2dad*.8 (x2d)
                   X3mom*.894
                   X3dad*.8 (x3d);
              M by M1mom*.894
                   M1dad*.8 (m1d)
                   M2mom*.894
                   M2dad*.8 (m2d)
                   M3mom*.894
                   M3dad*.8 (m3d);
              Y by Y1mom*.894
                   Y1dad*.8 (y1d)
                   Y2mom*.894
                   Y2dad*.8 (y2d)
                   Y3mom*.894
                   Y3dad*.8 (y3d);
              W by W1mom*.894
                   W1dad*.8 (w1d)
                   W2mom*.894
                   W2dad*.8 (w2d)
                   W3mom*.894
                   W3dad*.8 (w3d);

              ! M-1 method factors
              Xdad by X1dad*.4 (xdad1)
                      X2dad*.4 (xdad2)
                      X3dad*.4 (xdad3);
              Mdad by M1dad*.4 (mdad1)
                      M2dad*.4 (mdad2)
                      M3dad*.4 (mdad3);
              Ydad by Y1dad*.4 (ydad1)
                      Y2dad*.4 (ydad2)
                      Y3dad*.4 (ydad3);
              Wdad by W1dad*.4 (wdad1)
                      W2dad*.4 (wdad2)
                      W3dad*.4 (wdad3);

              !Intercepts - values based on application
              [X1mom*1.02 X2mom*0.88 X3mom*1.02 X1dad*1.01
              X2dad*0.90 X3dad*1.02];
```

```
[M1mom*1.03 M2mom*0.87 M3mom*0.99 M1dad*1.03
M2dad*0.86 M3dad*0.97];
[Y1mom*1.58 Y2mom*1.41 Y3mom*1.58 Y1dad*1.63
Y2dad*1.40 Y3dad*1.62];
[W1mom*0.98 W2mom*1.06 W3mom*1.04 W1dad*1.05
W2dad*1.07 W3dad*1.05];
[X@0 M@0 W@0 Y@0];

!Correlations not allowed
X with Xdad@0;
M with Mdad@0;
Y with Ydad@0;
W with Wdad@0;
!Corr between methods and common traits not
of same method - based on application
Xdad with M*.10 Y*.10 W*.08;
Mdad with X*.18 Y*.02 W*.13;
Ydad with X*.13 M*.03 W*.22;
Wdad with X*.04 M*.07 Y*.12;
!Correlation between X and W
X with W*0.5 (cov);
!Correlation between method factors
Xdad with Wdad*0.2 Mdad*0.2 Ydad*0.2;
Wdad with Mdad*0.2 Ydad*0.2;
Mdad with Ydad*0.2;

!Variances
X1mom*.2 X1dad*.2 X2mom*.2 X2dad*.2 X3mom*.2
X3dad*.2;
W1mom*.2 W1dad*.2 W2mom*.2 W2dad*.2 W3mom*.2
W3dad*.2;
M1mom*.2 M1dad*.2 M2mom*.2 M2dad*.2 M3mom*.2
M3dad*.2;
Y1mom*.2 Y1dad*.2 Y2mom*.2 Y2dad*.2 Y3mom*.2
Y3dad*.2;
X@1 Xdad@1;
W@1 Wdad@1;
M*.7892 (varM);
Mdad@1;
Y*.8815 (varY);
Ydad@1;

!Moderated mediation effects based on lit
review
M on X*0.275 (a1);
M on W*0.255 (a2);
```

```
               M on XxW*0.147 (a3);
               Y on M*0.235 (b);
               Y on X*0.194 (c);

Model          NEW(INDEXMM*.035 P2SDW*.134 P1SDW*.099
constraint:    MEANW*.064 N1SDW*.030 N2SDW*-.0045
               X1MVtau*.2 X2MVtau*.2 X3MVtau*.2
               M1MVtau*.2 M2MVtau*.2 M3MVtau*.2
               Y1MVtau*.2 Y2MVtau*.2 Y3MVtau*.2
               W1MVtau*.2 W2MVtau*.2 W3MVtau*.2);
               ! W =1, W removed from equation
               INDEXMM = a3*b;
               P2SDW = (a1 + a3*2) * b;
               P1SDW = (a1 + a3*1) * b;
               MEANW = (a1 + a3*0) * b;
               N1SDW = (a1 - a3*1) * b;
               N2SDW = (a1 - a3*2) * b;
               !proportion of true variance due to method
               effect
               X1MVtau = xdad1^2 / (xdad1^2 + x1d^2);
               X2MVtau = xdad2^2 / (xdad2^2 + x2d^2);
               X3MVtau = xdad3^2 / (xdad3^2 + x3d^2);
               W1MVtau = wdad1^2 / (wdad1^2 + w1d^2);
               W2MVtau = wdad2^2 / (wdad2^2 + w2d^2);
               W3MVtau = wdad3^2 / (wdad3^2 + w3d^2);
               M1MVtau = mdad1^2 / (mdad1^2 + m1d^2);
               M2MVtau = mdad2^2 / (mdad2^2 + m2d^2);
               M3MVtau = mdad3^2 / (mdad3^2 + m3d^2);
               Y1MVtau = ydad1^2 / (ydad1^2 + y1d^2);
               Y2MVtau = ydad2^2 / (ydad2^2 + y2d^2);
               Y3MVtau = ydad3^2 / (ydad3^2 + y3d^2);

               !assuring variances remain equal to 1
               0 = a1^2+a2^2+2*a1*a2*cov+varM - 1;
               0 = b^2*(a1^2+a2^2+2*a1*a2*cov+varM)+
               c^2+2*a1*b*c+varY - 1;

Output:        sampstat tech9;
```

**Example Code for Incorrect Model Specification**

```
Title:         M4 Model

Montecarlo:    names are X1mom X2mom X3mom X1dad X2dad X3dad
                         M1mom M2mom M3mom M1dad M2dad M3dad
```

```
          Y1mom Y2mom Y3mom Y1dad Y2dad Y3dad
          W1mom W2mom W3mom W1dad W2dad
W3dad;
nobservations = 200; !sample size
nreps = 500; !number of replications
seed = 84780;

MODEL POPULATION:
XxW | X XWITH W; !create interaction term

! MTMM Model Con = .8, Mspe = .2
X by X1mom*.894 X1dad*.8 X2mom*.894 X2dad*.8
X3mom*.894 X3dad*.8;
M by M1mom*.894 M1dad*.8 M2mom*.894 M2dad*.8
M3mom*.894 M3dad*.8;
Y by Y1mom*.894 Y1dad*.8 Y2mom*.894 Y2dad*.8
Y3mom*.894 Y3dad*.8;
W by W1mom*.894 W1dad*.8 W2mom*.894 W2dad*.8
W3mom*.894 W3dad*.8;

! M-1 method factors
Xdad by X1dad*.4 X2dad*.4 X3dad*.4;
Mdad by M1dad*.4 M2dad*.4 M3dad*.4;
Ydad by Y1dad*.4 Y2dad*.4 Y3dad*.4;
Wdad by W1dad*.4 W2dad*.4 W3dad*.4;

!Intercepts - values based on application
[X1mom*1.02 X2mom*0.88 X3mom*1.02 X1dad*1.01
X2dad*0.90 X3dad*1.02];
[M1mom*1.03 M2mom*0.87 M3mom*0.99 M1dad*1.03
M2dad*0.86 M3dad*0.97];
[Y1mom*1.58 Y2mom*1.41 Y3mom*1.58 Y1dad*1.63
Y2dad*1.40 Y3dad*1.62];
[W1mom*0.98 W2mom*1.06 W3mom*1.04 W1dad*1.05
W2dad*1.07 W3dad*1.05];
[X@0 M@0 W@0 Y@0];

!Correlations not allowed
X with Xdad@0;
M with Mdad@0;
Y with Ydad@0;
W with Wdad@0;
!Corr between methods and common traits not
of same method - based on application
Xdad with M*.10 Y*.10 W*.08;
Mdad with X*.18 Y*.02 W*.13;
```

```
                Ydad with X*.13 M*.03 W*.22;
                Wdad with X*.04 M*.07 Y*.12;
                !Correlation between X and W
                X with W*0.5;

                !Correlation between method factors
                Xdad with Wdad*0.2 Mdad*0.2 Ydad*0.2;
                Wdad with Mdad*0.2 Ydad*0.2;
                Mdad with Ydad*0.2;

                !Variances - standardized
                X1mom*.2 X1dad*.2 X2mom*.2 X2dad*.2 X3mom*.2
                X3dad*.2;
                W1mom*.2 W1dad*.2 W2mom*.2 W2dad*.2 W3mom*.2
                W3dad*.2;
                M1mom*.2 M1dad*.2 M2mom*.2 M2dad*.2 M3mom*.2
                M3dad*.2;
                Y1mom*.2 Y1dad*.2 Y2mom*.2 Y2dad*.2 Y3mom*.2
                Y3dad*.2;
                X@1 Xdad@1;
                W@1 Wdad@1;
                M@.7892 Mdad@1;
                Y@.8815 Ydad@1;

                !Moderated mediation effects based on lit
                review
                M on X*0.275 (a1);
                M on W*0.255 (a2);
                M on XxW*0.147 (a3);
                Y on M*0.235 (b);
                Y on X*0.194 (c);

Analysis:       type = RANDOM;
                algorithm = INTEGRATION;
                estimator = ML;

Model:          XxW | X XWITH W; !create interaction term

                ! MTMM Model - Con = .8, Mspe = .2
                X by X1mom*.894
                     X1dad*.8 (x1d)
                     X2mom*.894
                     X2dad*.8 (x2d)
                     X3mom*.894
                     X3dad*.8 (x3d);
                M by M1mom*.894
```

```
      M1dad*.8 (m1d)
      M2mom*.894
      M2dad*.8 (m2d)
      M3mom*.894
      M3dad*.8 (m3d);
Y by Y1mom*.894
      Y1dad*.8 (y1d)
      Y2mom*.894
      Y2dad*.8 (y2d)
      Y3mom*.894
      Y3dad*.8 (y3d);
W by W1mom*.894
      W1dad*.8 (w1d)
      W2mom*.894
      W2dad*.8 (w2d)
      W3mom*.894
      W3dad*.8 (w3d);

! No M-1 method factors

!Intercepts - values based on application
[X1mom*1.02 X2mom*0.88 X3mom*1.02 X1dad*1.01
X2dad*0.90 X3dad*1.02];
[M1mom*1.03 M2mom*0.87 M3mom*0.99 M1dad*1.03
M2dad*0.86 M3dad*0.97];
[Y1mom*1.58 Y2mom*1.41 Y3mom*1.58 Y1dad*1.63
Y2dad*1.40 Y3dad*1.62];
[W1mom*0.98 W2mom*1.06 W3mom*1.04 W1dad*1.05
W2dad*1.07 W3dad*1.05];
[X@0 M@0 W@0 Y@0];

!Correlation between X and W
X with W*0.5 (cov);

!Variances
X1mom*.2 X1dad*.2 X2mom*.2 X2dad*.2 X3mom*.2
X3dad*.2;
W1mom*.2 W1dad*.2 W2mom*.2 W2dad*.2 W3mom*.2
W3dad*.2;
M1mom*.2 M1dad*.2 M2mom*.2 M2dad*.2 M3mom*.2
M3dad*.2;
Y1mom*.2 Y1dad*.2 Y2mom*.2 Y2dad*.2 Y3mom*.2
Y3dad*.2;
X@1;
W@1;
M*.7892 (varM);
```

```
              Y*.8815 (varY);

              !Moderated mediation effects based on lit
              review
              M on X*0.275 (a1);
              M on W*0.255 (a2);
              M on XxW*0.147 (a3);
              Y on M*0.235 (b);
              Y on X*0.194 (c);

Model         NEW(INDEXMM*.035 P2SDW*.134 P1SDW*.099
constraint:   MEANW*.064 N1SDW*.030 N2SDW*-.0045);
              ! W =1, W removed from equation
              INDEXMM = a3*b;
              P2SDW = (a1 + a3*2) * b;
              P1SDW = (a1 + a3*1) * b;
              MEANW = (a1 + a3*0) * b;
              N1SDW = (a1 - a3*1) * b;
              N2SDW = (a1 - a3*2) * b;

              !assuring variances remain equal to 1
              0 = a1^2+a2^2+2*a1*a2*cov+varM - 1;
              0 = b^2*(a1^2+a2^2+2*a1*a2*cov+varM)+
              c^2+2*a1*b*c+varY - 1;

Output:       sampstat tech9;
```

# Kaylee Litson

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kaylee.litson@gmail.com


## Education

| | |
|---|---|
| 2019 (expected) | Ph.D. in Quantitative Psychology<br>Utah State University, Logan, UT<br>*Dissertation: A Structural Equation Modeling Approach Combining Multitrait-Multimethod Designs with Moderated Mediation Analysis* |
| 2012 | B.S. in Psychology<br>Dixie State University, St. George, UT<br>Honors: Summa Cum Laude, Valedictorian |

## Professional Positions

| | |
|---|---|
| 2018 – current | Graduate Research Assistant<br>Trajectories of Early Career Research, NSF grant 1760894<br>Instructional Technology and Learning Sciences<br>Utah State University, Logan, UT<br>Supervisor: David Feldon |
| 2016 – 2018 | Instructor<br>Department of Psychology<br>Utah State University, Logan, UT<br>Department head: Gretchen Peacock, Scott Bates |
| 2013 – 2017 | Presidential Doctoral Research Fellow<br>Latent Variable Analysis Lab<br>Department of Psychology<br>Utah State University, Logan, UT<br>Supervisor: Christian Geiser |

## Research Interests

- Moderated mediation analysis
- Latent state-trait analysis
- Multitrait-multimethod analysis
- Factor mixture modeling
- Cross-contextual behavior
- Longitudinal data analysis
- Cultural competence
- Graduate student education

## PUBLICATIONS

### *Peer Reviewed Journal Articles*

**Litson, K.**, Thornhill, C., Geiser, C., Burns, G. L., & Servera, M. (2019). Applying and interpreting mixture distribution latent state-trait models. *Structural Equation Modeling: A Multidisciplinary Journal.* Advance online publication. doi: 10.1080/10705511.2019.1575741

Seijas, R., Servera, M., García-Banda, G., Burns, G. L., Preszler, J., Barry, C. T., **Litson, K.**, & Geiser, C. (2018). Consistency of limited prosocial emotions across occasions, sources, and settings: Trait- or state-like construct in a young community sample? *Journal of Abnormal Child Psychology, 47*(1), 47-58. doi: 10.1007/s10802-018-0415-9. **3 citations**

**Litson, K.**, Geiser, C., Burns, G. L., & Servera, M. (2017). Examining trait × method interactions using mixture distribution multitrait-multimethod models. *Structural Equation Modeling: A Multidisciplinary Journal, 24*(1), 31-51. doi: 10.1080/10705511.2016.1238307. **5 citations**

Preszler, J., Burns, G. L., **Litson, K.**, Geiser, C., Servera, M., & Becker, S. P. (2017). How consistent is sluggish cognitive tempo across occasions, sources, and settings? Evidence from latent state-trait modeling. *Assessment*. doi: 10.1177/1073191116686178. **6 citations**

Preszler, J., Burns, G. L., **Litson, K.**, Geiser, C., & Servera, M. (2016). Trait and state variance in oppositional defiant disorder symptoms: A multi-source investigation with Spanish children. *Psychological Assessment, 29*, 135-147. **APA journal, 8 citations**

**Litson, K.**, Geiser, C., Burns, G. L., & Servera, M. (2016). Trait and state variance in multi-informant assessments of ADHD and academic impairment in first-grade children. *Journal of Clinical Child and Adolescent Psychology*. doi = 10.1080/15374416.2015.1118693. **10 citations**

Papa, L., **Litson, K.**, Lockhart, G., Chassin, L., & Geiser, C. (2015). Analyzing mediation models with multiple informants: A new approach with an application in clinical psychology. *Frontiers in Psychology: Psychology for Clinical Settings, 6*, 1674. doi: 10.3389/fpsyg.2015.01674. **2 citations**

Geiser, C., **Litson, K.**, Bishop, J., Keller, B. T., Burns, G. L., Servera, M., & Shiffman, S. (2015). Analyzing person, situation, and person × situation interaction effects: Latent state-trait models for the combination of random and fixed situations. *Psychological Methods, 20*(2), 165-192. doi: 10.1037/met0000026. **APA journal, 20 citations**

### *Journal Articles under Review*

Jeong, S., **Litson, K.**, Maierhofer, T., Castleberry, J., & Feldon, D. F. (in review). Assessment of open-ended problem solving during simulation: Development and evaluation of a wastewater treatment plant training system. *Educational Technology Research and Development.*

Jeong, S., **Litson, K.**, Blaney, J., & Feldon, D. (in review). Shifting gears: Characteristics and consequences of latent class transitions in doctoral socialization. *Research in Higher Education*.

Domenech Rodríguez, M. M., Reveles, A. K., **Litson, K.**, & Patterson, C. (in review). Development of the Awareness, Skills, Knowledge: General (ASK-G) Scale for measuring cultural competence in general populations. *Journal of Multicultural Counseling and Development*.

## Scholarly Presentations

**Litson, K.**, & Feldon, D. F. (2019, August). *Controlling for state variability in performance-based measures of Ph.D. research skill development.* Poster accepted for presentation in the Division 15 (Educational Psychology) program at the 2019 Annual Convention of the American Psychological Association, Chicago, IL.

**Litson, K.**, Blaney, J., & Feldon, D. F. (2019, April). *Identifying critical points for research self-efficacy stability: Considering the experiences of underrepresented minority, women, and first-generation doctoral students over time.* Paper presented at the 2019 Annual Meeting of the American Educational Research Association, Toronto, Canada.

Jeong, S., **Litson, K.**, & Feldon, D. F. (2019, April). *Role of doctoral training environments in scholarly productivity: Moderation from sense of belonging and research self-efficacy*. Paper presented at the 2019 Annual Meeting of the American Educational Research Association, Toronto, Canada.

Speed, E., **Litson, K.**, Covington, B., Nield, T., Henrie, T., & Jordan, K. (2019, April). *Automaticity of place value processing in dual language immersion second graders*. Poster presented at the Rocky Mountain Psychological Association, Denver, CO.

Jeong, S., Blaney, J., Feldon, D. F., & **Litson, K.** (2018, November). *Profiling students' faculty and peer interactions during the first three years of doctoral study: Associations with student demographics, sense of belonging, and research productivity*. Paper presented at the 43rd Annual Meeting of the Association for the Study of Higher Education, Tampa, FL.

Domenech Rodríguez, M. M., Reveles, A. K., & **Litson, K.** (2018, October). *Development of a measure to assess cultural competence in the general population.* Poster presented at the biennial conference of the National Latina/o Psychological Association. La Jolla, CA.

**Litson, K.**, Geiser, C., & Burns, G. L. (2017, May). *Multimethod moderated mediation analysis using a categorical multigroup design*. Paper presented at the 2017 Modern Modeling Methods Conference, Storrs, CT.

**Litson, K.**, Geiser, C., Burns, G. L., & Servera, M. (2016, July). *A multitrait-multimethod factor mixture model to assess trait × method interactions.* Poster presented at the 81st International Meeting of the Psychometric Society, Asheville, NC.

Preszler, J., Burns, G. L., **Litson, K.**, Geiser, C., & Servera, M. (2016, August). *Trait and state variance in oppositional defiant disorder symptoms: A multi-source investigation with Spanish children*. Paper presented at the 124th Annual Convention of the American Psychological Association, Denver, CO.

**Litson, K.,** & Geiser, C. (2015, April). *Using mixture distribution multitrait-multimethod analysis to assess trait × method interaction effects: An application in ADHD research.* Paper presented at the 2015 Utah State University Student Research Symposium, Logan, UT.

Geiser, C., **Litson, K.**, Bishop, J., & Burns, G. L. (2014, July). *Latent state-trait models for a combination of random and fixed situations.* Paper presented at the 79th International Meeting of the Psychometric Society, Madison, WI.

**Litson, K.**, Papa, L., Geiser, C., Lockhart, G., & Eid, M. (2014, July). *Mediation analysis using multimethod designs with structurally different and interchangeable methods: An application in personality psychology.* Paper presented at the 79th International Meeting of the Psychometric Society, Madison, WI.

**Litson, K.**, Geiser, C., Burns, G. L., & Servera, M. (2014, May). *An extended multimethod latent state-trait approach to assess consistency, occasion-specificity, and method effects of ADHD inattention, hyperactivity, and academic impairment.* Poster presented at the 2014 Modern Modeling Methods Conference, Storrs, CT.

Papa, L. A., **Litson, K.**, Geiser, C., & Lockhart, G. (2014, May). *A proposed model for mediation analysis with structurally different raters.* Poster presented at the 22nd Annual Meeting of the Society for Prevention Research, Washington, D.C.

Olson, K. J., Larsen-Rife, D., **Litson, K.**, Fossand, S., Mokiao, A., Oliver, D., & Abdollah, H. (2013, August). *The mediating effect of multicultural programming on diversity climate.* Poster presented in the Division 14 (I/O Psychology) program at the 121st Annual Convention of the American Psychological Association, Honolulu, HI.

**Litson, K.**, & Jones, J. (2013, April). *Increased levels of self-compassion correlates with reduced levels of aggression.* Paper presented at the 82nd Annual Convention of the Rocky Mountain Psychological Association, Denver, CO.

**Litson, K.**, & Larsen-Rife, D. (2012, April). *The effects of mindful awareness practices on affect regulation.* Poster presented at the 26th Annual National Conference on Undergraduate Research, Ogden, UT.

## Funding

### *Grants*

2017 – 2020 Principal Investigator, Long-Term Diversity Grant: US$15,000
"Safe Passages": Development and Application of a Cultural Competence Training Program and Mobile App
*Utah State University*

### *Grant Submissions (not funded)*

Litson, K. (2014, October). *Development and Application of MTMM Mixture Models to Study Trait × Method Interaction Effects.* Grant submitted to the National Science Foundation (NSF) Graduate Research Fellowship Program (GRFP), received Honorable Mention.

Litson, K. (2013, October). *How do Situational Factors Affect Human Behavior? Development and Application of New Methods for Studying Person-Situation Interactions.* Grant submitted to the NSF GRFP, not funded.

### *Fellowships & Scholarships*

2013 – 2017 Presidential Doctoral Research Fellowship
*Utah State University*

2010 – 2012 Chancellor Academic Scholarship
*Dixie State University*

2010 – 2012 Utah New Century Scholarship

*Dixie State University*

## Teaching Activities

| | |
|---|---|
| Fall 2018<br>Summer 2018 | Instructor<br>PSY 5330/6330: Principles of Psychological Measurement and Test Theory, online<br>*Utah State University* |
| Spring 2018<br>Fall 2017 | Instructor<br>PSY 3010: Psychological Statistics<br>*Utah State University* |
| Spring 2017 | Lab Instructor<br>PSY 3460: Neuroscience I<br>*Utah State University* |
| Fall 2016 | Lab Instructor<br>PSY 3010: Psychological Statistics<br>*Utah State University* |
| Fall 2014, 2015, 2016 | Instructor<br>USU 1010: Freshman Connections<br>*Utah State University* |
| Summer 2015 | Guest Lecturer for Correlation, Regression, and Chi-Square Analysis<br>PSY 3010: Psychological Statistics<br>*Utah State University* |
| 2011 – 2013 | Psychology, Mathematics & Statistics Tutor<br>*Dixie State University* |

## Professional Trainings

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|---|---|
| 2018 | Safe Passages 4 U Leader Training<br>*Description: Develop skills as a campus leader to lead Safe Passages 4 U cultural competence trainings.* |
| 2016, 2014 | Getting Started as a Successful Proposal Writer and Academician<br>*Description: Develop skills to start building an academic career and learn about the process of applying to major federal funding agencies.* |
| 2016 | Advancing Civility Interventions Trainer Training<br>*Description: Develop skills to teach middle and elementary school children how to address episodes of incivility at local schools.* |

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|---|---|
| 2016 | Love Your Data Workshop<br>*Description: Learn to create a data management plan.* |
| 2015 | Interfaith Initiative Training<br>*Description: Learn to create greater sense of connectedness across diversity of faith, culture, and tradition.* |
| 2015 | Effect Size & Power Analysis using G*Power Workshop<br>*Description: Use G*Power to perform statistical power analyses, and learn equations to compute effect sizes (Cohen's d, $\eta^2$, $r^2$, etc).* |
| 2014 | Allies Training<br>*Description: Show active support for the LGBTQ+ community, learn about LGBTQ+ issues, and support overall campus diversity.* |
| 2013 – 2014 | Research Scholars Certification Program (USU 6900)<br>*Description: Learn about the ethical treatment of human participants, conflicts of interest, collaborative science, data ownership, research misconduct, authorship and publication practices, and peer review.* |
| 2012 | Bacchus Gamma Certified Peer Educator Workshop<br>*Description: Learn to communicate about and facilitate others in creating healthy and safe campus environments.* |

## Community & Professional Service

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|---|---|
| 2017 – current | Founder & Student Leader<br>Safe Passages 4 U, Utah State University, Logan, UT<br>https://osf.io/zh5t2/<br>*Program was designed to increase self-awareness, knowledge, and skills about cultural competence. Program is currently being implemented at USU.* |
| 2016 – current | LGBTQA Mentor<br>Access & Diversity Center, Utah State University, Logan, UT |
| 2016 – 2017 | Co-Organizer and Committee Member<br>Logan Pride, Logan, UT |
| 2016 – 2017 | Community Outreach Presenter<br>Advancing Civility Interventions, Logan, UT<br>https://osf.io/p2a6s/ |
| 2015 | Student Representative<br>Hiring Committee, USU Psychology Program, Logan, UT |
| 2011 – 2012 | President<br>Psychology Club, Dixie State University, St. George, UT |
| 2012 | Founder & Committee Member<br>Passport to College, Dixie State University, St. George, UT |

*Program was designed to help low SES elementary students develop skills to succeed in high school and college.*

## Honors & Awards

2015 — Honorable Mention
National Science Foundation Graduate Research Fellowship Program
*Project: Development and Application of MTMM Mixture Models to Study Trait × Method Interaction Effects*

2013 — Valedictorian, College of Humanities and Social Sciences
Dixie State University, St. George, UT

2013 — Outstanding Research Award
Rocky Mountain Psychological Association, Denver, CO

2012 — Student of the Semester in Psychology
Dixie State University, St. George, UT

2012 — Student of the Year in Psychology
Dixie State University, St. George, UT

## Ad Hoc Journal Reviewer

- SAGE Open
- European Journal of Psychological Assessment
- Assessment
- Journal of Personality Assessment
- Journal of the Royal Statistical Society

## Scientific & Statistical Software Proficiencies

- M*plus*
- R (base, ggplot2, MplusAutomation)
- G*Power
- Tableau
- SPSS
- Stata
- MS Excel