Integrating Mediation and Moderation to Advance Theory Development and Testing

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Objective The concepts and associated analyses of mediation and moderation are important to the field of psychology. Although pediatric psychologists frequently incorporate mediation and moderation in their theories and empirical research, on few occasions have we integrated mediation and moderation. In this article, conceptual reasons for integrating mediation and moderation are offered.

Method We illustrate a model that integrates mediation and moderation.

Results In our illustration, the strength of an indirect or a mediating effect varied as a function of a moderating variable.

Conclusions Clinical implications of the integration of mediation and moderation are discussed, as is the potential of integrated models to advance research programs in pediatric psychology.

Key words BMI; mediated moderation; mediation; moderated mediation; moderation.

The concepts and associated analyses of mediation and moderation are important to the field of pediatric psychology (Holmbeck, 1997). Delineation of mediators and moderators is a mark of maturity of a discipline (Frazier, Tix, & Barron, 2004; Judd, McClelland, & Culhane, 1995) because doing so extends research from bivariate relations to investigations of “how” (i.e., mediation) and “when” or “for whom” (i.e., moderation). More importantly, accurate identification of mediators and moderators advances clinical practice (Holmbeck, 1997; Rose, Holmbeck, Coakley, & Franks, 2004). The popularity of incorporating mediators and moderators in psychological research increased dramatically following the seminal work of Baron and Kenny (1986). Holmbeck (1997) illustrated the importance of mediators and moderators within the field of pediatric psychology.

Many previous writings on mediation and moderation focused on the distinction between moderators and mediators, as the terms are often confused and used interchangeably (e.g., Frazier et al., 2004; Holmbeck, 1997, 2002; Kraemer, Kiernan, Essex, & Kupfer, 2008; Muller, Judd, & Yzerbyt, 2005; Preacher & Hayes, 2004; Preacher, Rucker, & Hayes, 2007; Rose et al., 2004; Shrout & Bolger, 2002). This emphasis on distinction may be one reason why scholars often overlook the fact that the early seminal writings on mediation and moderation include discussion of how these processes may be integrated (e.g., Baron & Kenny, 1986; Holmbeck, 1997; Rose et al., 2004). In what follows, we discuss why and how integrating mediation and moderation can offer a more complete approximation of how real-world phenomena operate.

Mediation and Moderation

A sound understanding of both mediation and moderation is essential before considering how they can be integrated. For a thorough overview of these concepts, we refer the interested reader to reader-friendly and practical illustrations of mediation and moderation specific to the fields
of clinical child and pediatric psychology (Holmbeck, 1997, 2002).Mediators and moderators play some role in the relation between two other variables or constructs, namely, an independent variable (IV) or predictor and a dependent variable or criterion. In this document, we adopt the terms “predictor” and “criterion,” though our illustrations also apply to experimental designs in which an IV is manipulated.

A mediator accounts for or explains (at least partially) the relation between a predictor and a criterion. Mediators answer the questions of how or why a predictor influences a criterion. In the context of clinical research when the predictor is a treatment condition (treatment vs. control), mediating mechanisms offer explanations of why a treatment produces a causal effect on the outcome of interest. As a variable that is influenced by a predictor and subsequently influences a criterion, the proposed mediator functions as both a criterion and a predictor (see Figure 1a; Holmbeck, 1997). Although some perspectives espouse that a significant relation between a predictor and criterion is a prerequisite for mediation (e.g., Baron & Kenny, 1986), an emerging perspective is that indirect effects can be identified and relevant even in the absence of a significant direct relation between a predictor and criterion (cf. Rucker, Preacher, Tormala, & Petty, 2011; Shrout & Bolger, 2002).

An example of a mediational model is the Theory of Planned Behavior (Ajzen, 1991), which posits that future engagement in some behavior of interest (such as physical exercise) will depend on one’s perceptions of social norms (“Do my friends exercise?”), perceived control of behavior (“If I wanted to exercise, would I be able to?”), and attitudes about the target behavior (“Will exercise really benefit me?”). Ajzen (1991) postulated that these direct effects are mediated by behavioral intentions. That is, perceptions of norms, perceived control, and attitudes toward the behavior influence one’s behavioral intentions, which in turn impact likelihood of behavioral engagement.

A moderator is a variable that affects the relation between a predictor and criterion. As such, figures that depict moderation often show a path from the moderator to the arrow that represents the relation from the predictor to the criterion: The influence is on neither the predictor nor criterion alone, but rather on the relation between them (see Figure 1b). A moderator changes the strength or direction of the relationship between the predictor and criterion. In interaction terms, the effect of a predictor on the criterion depends on the level of the moderator. In this respect, a moderator variable answers the questions of when or for whom a given relation exists (Holmbeck, 1997).

An example of a moderational model is the work summarized by Schwebel and Barton (2005). A large body of literature indicates that child temperament interacts with parenting behaviors to predict pediatric injury risk. One constellation of a child risk factor is temperament. Children with approach-oriented tendencies, impulsivity, inattention, and aggression are at a higher risk of injury (e.g., Schwebel & Gaines, 2007). Parent supervision has been shown to moderate the link between child temperament and injury risk. Children with challenging temperaments are at a high risk of injury generally, but their risk of injury is attenuated in the context of high parental supervision; the presence of adequate parental supervision alters the link between child temperament and injury risk (e.g., Schwebel & Barton, 2005). Stated differently, parental supervision is important for protecting children from injuries, but it is particularly important for subgroups of children with very challenging temperaments.

Integrating Mediation and Moderation

There are two notions central to understanding why integrating mediation and moderation can offer a more complete understanding of a phenomenon than focusing solely on mediation or moderation (Karazsia, van Dulmen, Wong, & Crowther, 2013). First, mediation is not always a universal process. Just as bivariate relations may be moderated by a third variable, so too may the strength of a mediating relationship change as a function of some other variable. Second, oftentimes the process(es) through which moderating effects occur may be of considerable interest. Thus, scholars may wish to identify mediating mechanisms of a previously identified moderating effect (i.e., through what mediating processes does moderation occur?).

A review of the use of mediation and moderation in the Journal of Pediatric Psychology revealed >100 uses of mediation or moderation since the year 2000, but we found only five examples during this time span that considered the integration of mediation and moderation (Bearden, Feinstein, & Cohen, 2012; Guite, Walker, Smith, & Garber, 2000; Hains et al., 2007; Petty, Davis, Tkacz, Young-Hyman, & Waller, 2009; Schwebel & Barton, 2005, 2007). Therefore, the purpose of this article is to advance understanding of how mediation and moderation can be integrated. We then offer an illustration of a model in which the strength of a mediating pathway is moderated by another variable, followed by a discussion of ways in which integrating mediation and moderation may be useful for advancing research programs and clinical practice within the field of pediatric psychology.
Moderated Mediation

An implicit assumption often made by researchers analyzing basic mediation models is that the mediation process is universal. That is, it is assumed implicitly that the mediating mechanisms explain the relation between a predictor and criterion for the entire population that was sampled. However, it is plausible that the strength of mediating pathways vary as a function of some other individual difference, such as symptom severity or demographic characteristics. Importantly, a proposed moderator variable may alter the direction or strength of the path between the predictor and criterion, the predictor and mediator (i.e., path “a”), or the mediator and criterion (i.e., path “b”) (Hayes, 2013a).

In the original formulation of the previously mentioned Theory of Planned Behavior (Ajzen, 1991), the mediating role of intentions was thought to be universal. However, subsequent research revealed that not everyone who intends to engage in a behavior actually acts on these intentions. Rhodes and colleagues (e.g., Rhodes, Corneya, & Hayduck, 2002; Rhodes, Corneya, & Jones, 2005) demonstrated that personality constructs moderate the link between intentions and actual behavior engagement. Specifically, individuals higher in conscientiousness are more likely to engage in physical exercise after reporting strong intentions to do so (Rhodes et al., 2002). Thus, intentions mediated the strength of relationship between hypothesized predictors and actual exercise behavior, but the strength of the mediation effect varied as a function of one’s self-reported conscientiousness. This is an example of mediation that is moderated (see Figure 1c).

Figure 1. (a) Conceptual model of mediation. Note. The path between predictor and mediator is often referred to as path “a”; the path between mediator and criterion is often referred to as path “b.” (b) Conceptual model of moderation. (c) Example of moderated mediation (i.e., mediation that is moderated). (d) Example of mediated moderation (i.e., moderation that occurs through a mediating variable). Note. Figure adapted with permission from Schwebel and Barton (2005).
Mediated Moderation

The implicit assumption of a basic moderation model is that the moderating effect on the criterion is direct. However, just as the path of a predictor on some criterion of interest may be mediated by one or multiple variables, so too may moderating paths occur through one or more mediating variables. Schwebel and Barton (2005) summarized existing literature on children’s unintentional injury risk to propose a conceptual model explaining how parent and child risk factors interact to predict pediatric injury risk. Their model is an excellent illustration of how mediation and moderation can be integrated to develop testable hypotheses on the roles of multiple influences on behavior (see Figure 1d). Schwebel and Barton (2005) hypothesized that the interaction between child temperament and parental supervision described earlier is not direct. That is, the link between the parent–child interaction and pediatric injury risk may be explained by the way in which children interact with stimuli in their environment. Children who are not being supervised and who demonstrate difficult temperaments are much more likely to overestimate their physical abilities (i.e., they think they can do more physically than they actually can), which in turn places them at risk of incurring an injury. However, when a child with a challenging temperament is in a context where a caregiver is offering adequate supervision, the child’s estimations of physical abilities tend to be more accurate, thereby decreasing injury risk. Importantly, subsequent empirical research supported this model (Barton & Schwebel, 2007). We should note that some authors have recently suggested that models of mediated moderation be reframed as models of moderated mediation (see Edwards, 2009; Hayes, 2013a).

Multiple Mediators and Moderators

Importantly, neither mediated moderation nor moderated mediation applies only to cases with a single mediator and moderator. In any given model, multiple mediators or moderators may exist. Revisiting the application of the Theory of Planned Behavior to physical exercise, Rhodes and colleagues (2005) have actually demonstrated that different personality traits moderate different pathways in the model. For example, components of extraversion appear to moderate the association between perceived behavioral control and one’s intentions to engage in exercise behaviors. Although this research was conducted with adult populations, we illustrate it here because of the incorporation of multiple moderators and because it has been suggested that this theory be extended to pediatric populations (Wilson & Lawman, 2009).

Statistical Analysis

The concepts of mediation, moderation, and their integration enable the development of seemingly infinite plausible applications to specific areas of research, and they can be challenging to analyze appropriately. Holmbeck’s (1997, 2002) seminal works on the analysis of mediation and moderation make this apparent. In a basic moderational model, regression results are obtained, and then “post hoc probing” procedures are used to investigate the moderation effect. Post hoc probing involves creation of a regression equation and then estimating the predicted value of the criterion at various levels of the moderator (for a complete overview of post hoc probing, see Holmbeck, 2002).

For assessment of the indirect or mediating relations, Baron and Kenny (1986) advocated for a four-step process wherein the relation between the predictor and criterion is established (step 1), followed by the relation between the predictor and hypothesized mediator (step 2), and the relation between the mediator and the outcome (step 3). In the final step (step 4), the predictor and mediator are entered simultaneously, and mediation is demonstrated if the path between the predictor and criterion decreases substantially. Note that analysis of step 1 may not be necessary (see Shrout & Bolger, 2002). These steps are often referred to as an indirect assessment of mediation. An oft-used alternative or supplement to this approach is the widely used Sobel test (Sobel, 1982), which computes the indirect effect by multiplying the measured paths from predictor to mediator (path “a”) and from the mediator to criterion (path “b”) (i.e., the indirect or mediating effect is quantified directly). When this path differs from zero, then it can be concluded that an indirect or mediation relation exists.

While these analytic procedures are used widely, methodologists have raised concerns about them (e.g., Hayes, 2009). Two of these concerns include statistical power within the Baron and Kenny (1986) approach and a nonnormal sampling distribution within the Sobel test. With respect to statistical power, Preacher and Hayes (2004, 2008) noted that in large samples, the likelihood of the path between the predictor and criterion becoming nonsignificant in Step 4 of the Baron and Kenny approach is small. Thus, scholars may conclude that there is no mediation when in fact it exists (Type II error). Regarding the Sobel test, Preacher and Hayes (2004, 2008) explained that the sampling distribution of the product of “a” and “b” paths is usually nonnormal, particularly in small samples, again influencing the accuracy of conclusions based on this test.

Importantly, tools for overcoming these limitations exist. One such tool is a nonparametric bootstrapping
procedure that offers a direct test of mediation (Preacher & Hayes, 2004, 2008). As an alternative to the Sobel test, this bootstrapping procedure is accomplished by taking a large number of samples \((n > 1,000)\) from the original data and computing the product of paths “a” and “b.” A confidence interval can then be generated around the point estimate of the product of “a” and “b” (for specific details of this bootstrapping procedure and how the confidence interval and point estimates are calculated, please consult Preacher & Hayes, 2004, 2008). When this confidence interval does not contain zero, it can be concluded that there is an indirect or mediating effect. As discussed by Hayes (2009) and colleagues (Preacher & Hayes, 2004, 2008), this bootstrapping approach overcomes limitations of the widely used Baron and Kenny (1986) and Sobel (1982) approaches, thus yielding results that are more accurate and less influenced by sample size (Hayes, 2009; Preacher & Hayes, 2004, 2008).

An Illustration

Here, we provide a demonstration of how the integration of mediation and moderation can be applied in research relevant to pediatric psychologists. The prevalence of pediatric obesity and overweight has increased dramatically in the past 30 years, with recent estimates suggesting that 33.6 and 18.4% of US youth aged 12–19 years are currently considered overweight and obese, respectively (Ogden, Carroll, Kit, & Flegal, 2012). Studies have shown that having a higher body mass index (BMI), and hence a body that deviates to a greater extent from what is considered ideal, is associated with more body image dissatisfaction in children and adolescents (Taylor & Altman, 1997). Given the substantial health and psychosocial risks associated with obesity (e.g., Goran, Ball, & Cruz, 2003), there is significant pressure on obese adolescents to lose weight, and on their parents to help them lose weight. Although increased child weight status warrants a degree of parental concern and may motivate parents to implement strategies to reduce or regulate child weight, some well-intentioned parental practices may exacerbate the problem. Several studies have highlighted the role of maternal encouragement to diet in multiple negative psychosocial outcomes, such as disordered eating behaviors and body dissatisfaction (van den Berg, Keery, Eisenberg, & Neumark-Sztainer, 2010).

Although it is clear that child BMI, maternal encouragement to diet, and child body dissatisfaction are related, less attention has been paid to elucidating a model that depicts these relationships. For example, maternal encouragement to diet may mediate the association between child BMI and child body dissatisfaction. Further, it has been proposed that heavier parents may express their own body dissatisfaction, therefore providing opportunities for children to emulate these behaviors (Davidson & Birch, 2001). Therefore, the current study hypothesized that the indirect relation between child BMI and child body dissatisfaction will be moderated by parent BMI (i.e., moderated mediation). See Figure 2 for the graphical illustration of this hypothesized model.

Method

Participants

Participants were 117 children/adolescents between the ages of 8 and 17 years and a parent or legal guardian attending a regularly scheduled acute care or annual checkup appointment at a pediatric primary care clinic. Table I presents demographic data and descriptive statistics for all participants in present analyses.

Anthropometrics

A medical team assessed child height (cm) and weight (kg) during the primary care visit. BMI z-scores were calculated using this information (Kuczmarski et al., 2002). Parent BMI was calculated using parent self-reports of height and weight.

Maternal Encouragement to Diet

Youth perception of maternal encouragement to diet was measured using the question “[Over the past year] My mother encouraged me to diet to control my weight.” Responses were made using a 4-point Likert scale ranging from “strongly disagree” to “strongly agree,” with higher scores indicating more encouragement to diet. Similar one-item questions have been used to assess encouragement to diet in previous studies (Bauer, Laska, Fulkerson, & Neumark-Sztainer, 2011) and have been shown to be associated with weight loss strategies (McCabe & Ricciardelli, 2005) and to distinguish between women with and without bulimia (Moreno & Thelen, 1993).

Body Dissatisfaction

The Children’s Body Image Scale (Truby & Paxton, 2002) consists of pictorial scales for boys and girls, containing seven pictures of varying body size. Children were asked to identify the body figure most like their own (perceived figures) and the body figure they would most like to have (ideal figure). Following scoring instructions described by Truby and Paxton (2002), the difference between perceived and ideal figures was used as an index of body
dissatisfaction. Positive values result when the perceived figure is larger than the ideal figure and thus corresponds with a desire for a smaller body size. Negative values result when the ideal figure is larger than the perceived figure and corresponds with a desire for a larger body size. Previous research demonstrated good construct validity and test–retest reliability of this scale in samples of youth aged 7–17 years (Truby & Paxton, 2008).

Results

Preliminary screening revealed that all variables were sufficiently normally distributed. To evaluate the model in Figure 2, we used a PROCESS macro developed by Hayes (2013a) for SPSS (please note that the same package of statistics is also available for SAS). A description and visual depiction of each model that can be tested with PROCESS is available from Hayes (2013b). Basically, the macro is based on Ordinary Least Squares (OLS) regression and incorporates aforementioned bootstrapping procedures for investigating mediation. The current analysis was conducted using 5,000 bootstrapped samples. One benefit of PROCESS for the present analyses is that the macro automatically computes post hoc probing for moderating effects. The output will be straightforward to researchers familiar with OLS regression (see Appendix), with a summary of the model offered first, then the overall regression results, followed by post hoc probing.

In our analyses, the model was significant, $F(2, 116) = 15.62, p < .001$, accounting for 21.2% of variance in body dissatisfaction. With regard to predicting the outcome variable, maternal encouragement to diet (unstandardized coefficient $= .29, p = .04$) as well as child BMI z-score (unstandardized coefficient $= .47, p < .001$) emerged as a significant predictors of child body dissatisfaction. Evidence of moderation of the indirect effect by parent BMI was found in the significant interaction between child BMI z-score and parent BMI predicting maternal encouragement to diet (unstandardized coefficient $= .03, p < .01$), indicating that parent BMI moderated the relationship between youth BMI z-score and maternal encouragement to diet. Given that the “a” path of the mediation model is moderated, this means that the indirect effect will also be moderated. Results were then evaluated at five levels of parent BMI (corresponding to the 10th, 25th, 50th, 75th, and 90th percentiles in our sample), and a confidence interval was generated at each level of the proposed moderator. Where the confidence interval does not contain zero, it can be concluded that the indirect or mediating effect is significant. See Table II for the post hoc probing results at the different parent BMI levels.

In our model, maternal encouragement to diet emerged as a significant mediator between BMI z-score and body dissatisfaction. However, as can be seen in Table II, this mediating effect varied as a function of the proposed moderator. In other words, the mediating effect was not a universal process. Specifically, the indirect effect of BMI z-score on body dissatisfaction through maternal encouragement to diet was significant for youth who had parents who were overweight or obese (i.e., parent BMI $> 25$). However, maternal encouragement to diet was not a significant mediator of the relationship between BMI z-score and child body

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Table I. Demographics and Descriptive Statistics of the Study Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (SD)</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. BMI z-score</td>
<td>1.01 (1.12)</td>
<td>$-1.77, 3.27$</td>
</tr>
<tr>
<td>2. Child age</td>
<td>11.67 (2.57)</td>
<td>8, 17</td>
</tr>
<tr>
<td>3. Parent BMI</td>
<td>31.91 (8.4)</td>
<td>18.89, 53.74</td>
</tr>
<tr>
<td>4. Maternal encouragement to diet</td>
<td>1.96 (1.06)</td>
<td>1, 4</td>
</tr>
<tr>
<td>5. Body dissatisfaction</td>
<td>0.783 (1.57)</td>
<td>$-2, 8$</td>
</tr>
</tbody>
</table>

Note. BMI = body mass index.
ways to support healthy eating and exercise habits for diet behaviors and educating parents about effective include assessing and addressing maternal encouragement can also have important clinical applications. The examining the processes through which moderation occurs. Where moderation is established, researchers can begin ex-
might moderate the strength of the mediating effects. mediation process is universal, and if not, what factors tion is well-established, researchers can begin asking if the mediation analyses also fulfill these recommendations, (i.e., parent BMI <25).

Discussion

Holmbeck, Zebracki, and McGordon (2009) recently offered six recommendations for guiding pediatric psychologists in their applied statistical analyses. The concepts and associated statistical analyses of mediation, moderation, and their integration directly address three of these recommendations: (a) “...go beyond examining bivariate associations between predictors and outcomes...”; (b) “...examine the influence of moderators...”; (c) “...begin to theorize about variables that may explain (or mediate)...” (p. 67). While basic mediation and moderation analyses also fulfill these recommendations, we believe that pediatric psychologists can advance conceptualizations of their research areas by integrating mediation and moderation. That is the point that we wish to emphasize here. Advances in statistical analyses of mediation, moderation, and their integration have been developed over the past decade (e.g., Hayes, 2013a). We believe these analytical strategies will only be fruitful in the context of well-articulated conceptual paradigms. By integrating mediation and moderation, pediatric psychologists will be able to advance their research questions. For example, where mediation is well-established, researchers can begin asking if the mediation process is universal, and if not, what factors might moderate the strength of the mediating effects. Where moderation is established, researchers can begin examining the processes through which moderation occurs.

Considering the integration of mediation and moderation can also have important clinical applications. The clinical implications of the demonstration in this study include assessing and addressing maternal encouragement to diet behaviors and educating parents about effective ways to support healthy eating and exercise habits for adolescents. Additionally, practitioners should take into account parent weight when assessing maternal encouragement to diet, as it appears that parent weight is influential in predicting weight-related behaviors and attitudes. Had mediation been examined absent from the context of the proposed moderator, we may have concluded erroneously that the predictor-criterion relationship was relevant to all children. Instead, our analyses revealed that the context within which a child lives, which in this case was defined by parental weight status, plays an important role in the demonstrated relationships. Further, this finding supports current trends in obesity interventions, which have integrated parent weight management into family lifestyle intervention programs aimed at ultimately addressing childhood obesity (Epstein, 1996). More broadly, considering potential moderators in the context of established mediational models will offer a framework for tailoring interventions to specific subpopulations.

Limitations and Additional Considerations

The limitations of analyses of mediation, moderation, and their integration are linked inextricably to the research design underlying the analytical techniques. In our analyses, the data were cross-sectional, which may inflate estimations of mediation and precludes any conclusions of directionality (Maxwell & Cole, 2007). Causality cannot be assumed in the absence of experimental manipulation (which would actually be impossible for the predictor in our analyses). Further, assessment of the mediating variable was based on a single item that may not represent true properties interval or ratio data.

We need to note that the concepts and methods discussed in this article are not new. Therefore, there are no new assumptions or sample size issues to discuss. One benefit of the bootstrapping approach to moderation analyses is that it overcomes the requirement of “large” sample sizes of the Sobel approach to assessing mediation. That said, our analysis was still based on OLS regression, and thus corresponding assumptions and sample size issues still apply. Specific to mediation analyses, Fritz and MacKinnon (2007) offered empirically based estimates of sample sizes required to achieve adequate statistical power (which they operationalize as 0.8). Naturally, the sample size required to demonstrate significant results will vary as a function of effect size, with larger samples being necessary when the strength of relations among variables is smaller. According to Fritz and MacKinnon (2007), sample sizes necessary to achieve adequate power to detect mediating effects ranges can vary greatly. They report that only 34 participants are necessary when bootstrapping techniques are used in the context of strong associations (β = .59) between both the

Table II. 95% BC Confidence Intervals of the Indirect Effect at the 10th, 25th, 50th, 75th, and 90th Percentiles of the Moderator

<table>
<thead>
<tr>
<th>Parent BMI</th>
<th>Point estimate</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>21.4644</td>
<td>0.0670</td>
<td>-0.0344</td>
<td>0.2261</td>
</tr>
<tr>
<td>24.9936</td>
<td>0.1072</td>
<td>0.0131b</td>
<td>0.2691</td>
</tr>
<tr>
<td>29.2000</td>
<td>0.1549</td>
<td>0.0464a</td>
<td>0.3209</td>
</tr>
<tr>
<td>34.4331</td>
<td>0.2146</td>
<td>0.0642b</td>
<td>0.3919</td>
</tr>
<tr>
<td>44.6240</td>
<td>0.3301</td>
<td>0.0861b</td>
<td>0.5739</td>
</tr>
</tbody>
</table>

Note. BMI = body mass index.

*BC confidence intervals are bias-corrected.

Confidence intervals that do not contain zero are deemed to be significant.
predictor and mediator (path “a”) and between the mediator and criterion (path “b”). However, in the context of small associations ($\beta = .14$) for both the “a” and “b” paths, >500 participants are required when adopting the Baron and Kenny (1986) approach for assessing mediation. Notably, sample size requirements reported by Fritz and MacKinnon (2007) were always smaller when bootstrapping methods were used, but samples >450 may still be necessary when the strength of relations among variables is small. Naturally, more complex models that incorporate multiple mediators and moderators will require larger sample sizes.

In addition to sample size issues, researchers should be cognizant of statistical assumptions that underlie analytical approaches that they adopt. In our regression-based illustration, the same assumptions of OLS regression remain relevant. These include normality of residuals, homoscedasticity, and linearity. OLS regression tends to be a fairly robust technique when these assumptions are violated, particularly when the violations are relatively minor (e.g., Hayes, 2013a; Tabachnick & Fidell, 2013).

With respect to our adoption of the PROCESS macro, we would also like to discuss briefly some of the available extensions of PROCESS, as well as some of its limitations. We examined a continuous criterion in this illustration, but the macro is fully functional with dichotomous outcomes as well (i.e., logistic regression). Pediatric psychologists are often faced with distributions that are neither dichotomous nor normally distributed (such as ordinal data or count outcomes; Karazsia & van Dulmen, 2008), and in such situations, the regression analyses that incorporate mediation and or moderation will need to be conducted with an appropriate estimation method (e.g., Poisson regression, Probit regression) not currently available in PROCESS. When researchers test models with multiple outcome variables, PROCESS can be adapted accordingly (see Hayes, 2013a). However, PROCESS currently handles models for which the criterion is observed. This limitation is relevant to pediatric psychologists who may model latent (unobserved) variables. Alternative analytic approaches, such as Structural Equation Modeling (SEM), offer the flexibility for testing such models (see Nelson, Aylward, & Steele, 2008, for overview of the relevance of SEM to pediatric psychologists). Although modeling interaction terms can introduce a degree of complexity in SEM (Edwards, 2009), step-by-step resources applicable to SEM software do exist for examining both mediation and moderation (Little, Card, Bovaird, Preacher, & Crandall, 2007).

In light of limitations of our demonstration in this article, we hope that our illustration inspires pediatric psychologists to consider ways in which their research programs and clinical practices might be advanced by being cognizant of the ways in which mediation and moderation may be integrated. The reader interested in integrating mediation and moderation in her own work is encouraged to consult sources referenced throughout this document.

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Conflicts of interest: None declared.

**Appendix**

Run MATRIX procedure:

```
************************ PROCESS Procedure for SPSS Release 2.041 ****************
Written by Andrew F. Hayes, Ph.D. http://www.afhayes.com
**************************************************************************
Model = 7
Y = BodyDiss
X = BMIZHD
M = MomETDHD
W = Parent_B
Sample size
117
*************************** ****************************************************
Outcome: MomETDHD
Model Summary
R       R-sq          F        df1        df2          p
.5687      .3234    18.0028     3.0000   113.0000      .0000
Model
 coeff         se          t          p       LLCI       ULCI
constant     2.1069      .4255     4.9520      .0000     1.2640     2.9498
BMIZHD       -.4557      .2939    -1.5503      .1239    -1.0380      .1266
Parent_B     -.0216      .0142    -1.5223      .1307     -.0497      .0065
int_1         .0293      .0091     3.2013      .0018      .0112      .0474
```

(Continued)
Appendix (Continued)

DIRECT EFFECT OF X ON Y

Interaction:

<table>
<thead>
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<th>int_1</th>
<th>BMIZHD</th>
<th>X</th>
<th>Parent_B</th>
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Outcome: BodyDiss

Model Summary

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<th>F</th>
<th>df1</th>
<th>df2</th>
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Model

<table>
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<td>.0083</td>
<td>.1018</td>
</tr>
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<td>.1369</td>
<td>3.2952</td>
<td>.0013</td>
<td>.1799</td>
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</table>

DIRECT AND INDIRECT EFFECTS

Direct effect of X on Y

<table>
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<tr>
<th>Effect</th>
<th>SE</th>
<th>t</th>
<th>p</th>
<th>LLCI</th>
<th>ULCI</th>
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</thead>
<tbody>
<tr>
<td>MomETDHD</td>
<td>.0670</td>
<td>.0631</td>
<td>-.0344</td>
<td>.2261</td>
<td></td>
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<tr>
<td>MomETDHD</td>
<td>.1072</td>
<td>.0627</td>
<td>.0131</td>
<td>.2691</td>
<td></td>
</tr>
<tr>
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<td>.1549</td>
<td>.0686</td>
<td>.0464</td>
<td>.3209</td>
<td></td>
</tr>
<tr>
<td>MomETDHD</td>
<td>.2146</td>
<td>.0836</td>
<td>.0642</td>
<td>.3919</td>
<td></td>
</tr>
<tr>
<td>MomETDHD</td>
<td>.3301</td>
<td>.1245</td>
<td>.0861</td>
<td>.5759</td>
<td></td>
</tr>
</tbody>
</table>

Conditional indirect effect(s) of X on Y at values of the moderator(s)

<table>
<thead>
<tr>
<th>Mediator</th>
<th>Parent_B</th>
<th>Effect</th>
<th>Boot SE</th>
<th>BootLLCI</th>
<th>BootULCI</th>
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<td>.0861</td>
<td>.5759</td>
</tr>
</tbody>
</table>

Values for quantitative moderators are 10th, 25th, 50th, 75th, and 90th percentiles.

Values for dichotomous moderators are the two values of the moderator.

ANALYSIS NOTES AND WARNINGS

Number of bootstrap samples for bias corrected bootstrap confidence intervals: 5000

Level of confidence for all confidence intervals in output: 95.00

END MATRIX

References


