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Cover Page Footnote

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Moderated Mediation Analysis: A Review and Application to School Climate Research

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Moderated mediation analysis is a valuable technique for assessing whether an indirect effect is conditional on values of a moderating variable. We review the basis of moderation and mediation and their integration into a combined model of moderated mediation within a regression framework. Thereafter, an analytic and interpretive illustration of the technique is provided in the context of a substantive school climate research question. The illustration is based on a sample of 318 high schools that examines whether school-wide student engagement mediates the association between the prevalence of teasing and bullying (PTB) and academic achievement on a state-mandated reading exam; and whether this indirect effect was moderated by student perceptions of teacher support.

Contemporary research questions in the social sciences increasingly involve complex relationships among multiple variables that operate in concert. Some of these complexities arise when variable associations are conditional on other variables. For example, *when* the relationship between social support and adolescent mental health changes across levels of academic achievement (Stewart & Suldo, 2011); or when the association between pre-kindergarten school-readiness skills and later academic achievement among low-income Black children differs between immigrant and non-immigrant status (Calzada et al., 2015). In other instances, variable associations might be best understood in the presence of an intervening, or mediating, variable that illuminates how or why other variables are related. For example, Fredrick and Demaray (2018) demonstrated that peer victimization led to depressive symptoms, which in turn resulted in suicidal ideation. Inclusion of depression as a mediating variable in this work allowed for a more complete understanding of 'how' peer victimization was related to suicidal ideation. Other substantive examples of mediation analysis can be found in Fantuzzo et al. (2012); Mittleman (2018); Purpura et al. (2013); Raver et al. (2011); and Ruzek et al. (2016).

Moderation and mediation analyses are two commonly used techniques to address questions of when and why variables are related, respectively. Moderation occurs when the magnitude and/or direction of a relationship between variables is conditional on a third variable, and tests of moderation can be useful for evaluating the boundary conditions under which associations between two (or more) variables occur (Aguinis, 2004). In other words, whether variable associations hold across different situations or for different groups of people. By contrast, mediation analysis provides a means to test how or why two or more variables might be related. A mediating variable can be conceptualized as a third variable that intervenes in the relationship between two or more other variables, acting as a mechanism, through which one variable's effect is transmitted to another (Baron & Kenny, 1986).

Although moderation and mediation are each useful on their own, integrating both into a single model enables researchers to examine even more nuanced relationships among variables. These combined forms are commonly referred to as *moderated mediation* or *conditional process models* (Hayes & Preacher, 2013), and allow for evaluations of whether an indirect effect is moderated by another variable. Moderated mediation models are particularly useful when there is interest in understanding both why and under what conditions variables are related to one another. This combined model provides an opportunity to simultaneously investigate contingent and indirect effects. For example, one recent study examined the moderating effect of certain genetic markers on the indirect effect of parenting behavior on children's ADHD symptoms through neurocognitive functioning (Morgan et al., 2018). Results indicated that positive parental praise actually impaired children's neurocognitive functioning during a battery of tasks, which then resulted in more pronounced ADHD symptoms. However, this indirect effect was moderated by two genetic polymorphisms, such that the strength of the mediating effect varied across children with different genotypes. As this example illustrates, the use of moderated mediation allowed for an evaluation of how neurocognitive functioning mediated the relationship between parenting behavior and ADHD symptoms, and for whom this occurred (i.e., different genetic marker groups).

While other recent applications of moderated mediation can be found in Dicke et al. (2014); Guo et al. (2018); and O'Neal et al. (2018), the use of these models is far less prevalent in the social sciences than are uses of moderation or mediation by themselves. In the sections below we briefly review methods for conducting moderation and mediation, and describe their integration for testing moderated mediating effects. Thereafter, we illustrate the usefulness and application of the approach in the context of education research. Given continued interest in providing students with healthy learning environments and its importance in national policy (e.g., the 2015 Every Student Succeeds Act, Public Law 114-95), we examine the role of student engagement in mediating the association between the prevalence of bullying in schools and academic achievement, and we test whether these relationships are moderated by levels of supportive school climate. In doing so, we describe the interpretable elements of the model to motivate more widespread use of this analytic approach and provide the PROCESS code used to estimate the model in SPSS.

Moderation analysis

A linear model that evaluates the relationship between two continuous regressors (X and W) and a single outcome (Y) can be expressed as

$$Y = i_Y + b_1X + b_2W \tag{1}$$

where the unstandardized form of b_1 represents the expected change in Y for a unit increase in X, b_2 represents the expected change in Y for a unit change in W, and i_Y is an estimate of the expected value of Y when X and W are equal to zero. Importantly, the relationship (b) between a regressor (e.g., X) and Y holds across all values of the other regressor (e.g., W) in this additive form of the equation. The viability of b representing the amount of Y change for a unit change in its associated regressor, across all points of the other regressor in the model, can be evaluated through inclusion of a product term of the two regressors (XW) into Equation 1:

$$Y = i_Y + b_1X + b_2W + b_3XW \tag{2}$$

Equation 2 is graphically represented in Figure 1A. Here, b_3 estimates the amount of change in b_1 for a unit increase in W, or conversely, how b_2 changes across values of X. A non-zero b_3 term indicates that the Y,X or Y,W relationships are not constant across levels of the other regressor. A non-zero b_3 coefficient signals the presence of a *moderating effect* (Saunders, 1956), or *interaction* (Cohen, 1968), where the relationship between two variables is conditional on a third variable. Establishing a significant relationship between two variables is not a necessary pre-condition to testing for moderation, as evidence of an association between two variables may sometimes only be found when considered in the context of a third moderating variable (Aguinis, 2004). Tests of moderation can be particularly useful for evaluating whether relationships hold across situations, settings, and people.

Mediation analysis

Although the concept of intervening variables pre-dates the seminal works of Kenny and colleagues (Baron & Kenny, 1986; Judd & Kenny, 1981), their contributions helped to establish statistical mediation analysis in the methods literature as well as promote its use by applied researchers. Judd and Kenny (1981) recommended evaluating mediation hypotheses through a series of regression equations, an approach they termed *process analysis*. They outlined three conditions that must hold in order to validate a proposed mediation effect: (1) the treatment affects the outcome, (2) the treatment affects the mediator, and (3) the treatment does not affect the outcome when controlling for the mediator. These conditions were tested by three regression equations: regressing the outcome on the treatment variable, regressing the mediator on the treatment variable, and regressing the outcome on both the mediator and treatment variable.

Baron and Kenny (1986) restated and expanded upon Judd and Kenny's guidelines, further popularizing the so-called *causal steps approach* to mediation. As outlined in Baron and Kenny, the first step was to estimate the *total effect* of X on Y,

$$Y = i_Y + cX \quad (3)$$

where i_Y is the intercept, and the coefficient c is the slope. The upper model in Figure 1B illustrates the total effect of X on Y (path c). After estimating a statistically significant total effect, the second step was to establish that X was related to M, as depicted by path *a* in the lower model in Figure 1B:

$$M = i_M + aX \quad (4)$$

The third step was to show that M was associated with Y when controlling for X, as represented by path *b* in Figure 1B:

$$Y = i_Y + c'X + bM \quad (5)$$

The final step required estimation of the *direct effect* of X on Y, holding M constant (path c′ in Figure 1B, and coefficient c' in Equation 5).

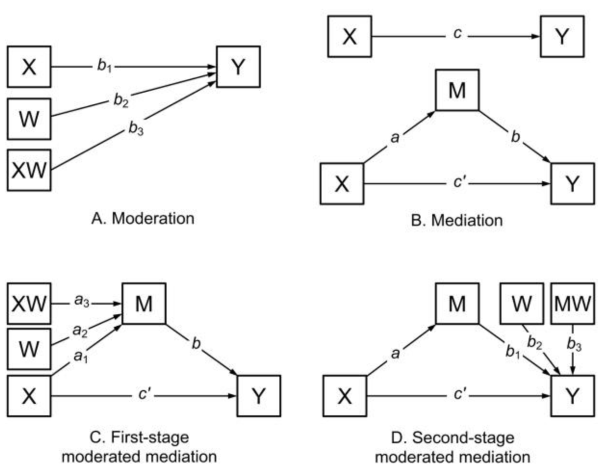

Figure 1. Statistical diagrams of moderation, mediation (total effect model on top and mediation model on bottom), first-stage moderated mediation, and second-stage moderated mediation.

In school psychology research, for example, Fairchild and McQuillin (2010) found that the majority of mediation studies in three of the field's top journals followed the causal steps approach. However, the methodological field has moved away from this approach as more recent advances in mediation analysis have been developed (e.g., Hayes, 2009; MacKinnon et al., 2002; Rucker et al., 2011; Shrout & Bolger, 2002; Zhao et al., 2010). While Baron and Kenny's (1986) method used a series of hypothesis tests to assess mediation, contemporary approaches focus directly on quantifying the indirect effect of X on Y through the mediator. This indirect effect is estimated as the product of the effect of X on M and the effect of M on Y, represented by paths a and b in Figure 1B. By substituting Equation 4 into Equation 5, the mediation model can be expressed as a single equation:

$$Y = i_Y + c'X + bi_M + abX \quad (6)$$

The *ab* product term quantifies the estimated change in the outcome that results from a one-unit change in the independent variable through the mediator.

Through OLS regression, the indirect effect is equal to the total effect minus the direct effect, $ab = c - c'$ (MacKinnon et al., 1995). This equivalence is noteworthy because it highlights an important flaw in the assumptions underlying the causal steps logic. According to the causal steps approach, if there is no significant association between the independent and dependent variables, the analysis stops, and mediation is said to be non-existent. Although intuition may suggest that there must be a total effect of X on Y in order for an indirect effect to exist, mathematically it is not the case. When a significant indirect effect *ab* and a significant direct effect c' have opposite signs, they can cancel each other out, such that their sum (the total effect c) is not significantly different from zero (MacKinnon et al., 2002). Thus, researchers following the causal steps approach could mistakenly dismiss the presence of mediation. In light of this, methodologists today no longer require evidence of an association between X and Y as a pre-condition for evaluating the presence of a mediating effect.

Another requirement for mediation using the causal steps approach that is no longer considered necessary today is the notion of full mediation. In the methodological literature, a distinction is made between *fully* and *partially* mediated models. When the direct effect c' of X on Y, controlling for M, is zero, and the indirect effect is statistically greater than zero, the combined results could be said to support full mediation (Baron & Kenny, 1986; Judd & Kenny, 1981). Justification for full mediation requires that all mediating pathways between X and Y have been identified and that they completely account for the X-Y association. By contrast, when both the direct and indirect effects are statistically significant, the results are said to support partial mediation because the mediating variable only accounts for part of the relationship between X and Y.

Evaluating the statistical significance of a mediating effect has been an active area of research in recent years. Historically, researchers have relied on the Sobel test (i.e., delta method or normal theory approach; Sobel, 1982). This procedure generates a standard error from the *ab* indirect effect sampling distribution that is, in turn, used as the basis for a test statistic or confidence interval. An assumption of the Sobel test is that the sampling distribution of *ab* is normal; however, the sampling distribution of a product of two normally distributed variables is not necessarily normally distributed (Aroian, 1947). Simulation studies have demonstrated that the Sobel test is less powerful than alternative methods when the indirect effect is nonzero and has a skewed distribution, particularly for small sample sizes of less than 100 (Hayes & Scharkow, 2013; MacKinnon et al., 2004; Preacher & Selig, 2012; Shrout & Bolger, 2002).

By contrast, bootstrap confidence intervals (Preacher & Hayes, 2004, 2008; Shrout & Bolger, 2002) and Monte Carlo confidence intervals (MacKinnon et al., 2004; Preacher & Selig, 2012) avoid this problem by not assuming a normal sampling distribution. Introduced by Bollen and Stine (1990), and further discussed in Lockwood and MacKinnon (1998), the bootstrap approach for inferences regarding indirect effects has become one of the more popular techniques in the mediation methods literature. Here, a random sample is repeatedly drawn with replacement from the analytic sample, and estimates of *ab* are obtained for each bootstrap sample with the goal of developing a confidence interval for the indirect effect. Resampling is typically done thousands of times, resulting in k estimates of *ab*, which are used as an empirical sampling distribution of the statistic. A $(1 - \alpha)$ percentile confidence interval for the indirect effect is calculated using the limits of the $100(1 - \alpha)\%$ of the bootstrap distribution (Bollen & Stine, 1990). Confidence intervals that do not contain zero support the claim that M mediates X's effect on Y. As discussed in Preacher and Selig (2012), more complex variations of the bootstrap-based technique include bias-corrected, bias-corrected and accelerated, residual based, and parametric based procedures. The advantage of the bootstrap procedure over the Sobel test is that it does not assume normality, it can accommodate small sample sizes, and is adaptable to more complex models (Hayes, 2009).

Monte Carlo methods for creating confidence intervals for indirect effects involve using the sample estimates, $\hat{a}$ and $\hat{b}$ and their asymptotic variances and covariances to simulate a sampling distribution of *ab* based on repeated random draws from a defined multinormal distribution, rather than from resampling (MacKinnon et al., 2004). A confidence interval for *ab* is then calculated, as described previously for the bootstrap method. Like bootstrap procedures, the Monte Carlo method makes no parametric assumptions about the distribution of *ab*. Theoretically both approaches provide a useful pathway for evaluating indirect effects. Currently, however, only the Monte Carlo approach has been developed for applications in multilevel contexts. (Bauer et al., 2006; Preacher & Selig, 2012).

Mediation analysis in a regression-based framework relies upon the same model assumptions that are typical of OLS general linear models. It is assumed that the residuals are normally distributed, independent, and that homoscedasticity holds (Williams et al., 2013). In addition, it is worth noting that when conducting mediation analysis there is an implied assumption of temporal precedence. That is, the assumption that X precedes M, which precedes Y. This strong assumption cannot be met when mediation analysis is conducted with cross-sectional data. As a result, causal inferences about mediation should not be made with cross-sectional data. In fact, some methodologists reserve the term *mediation* for causal interpretations based exclusively on longitudinal designs (Little, 2013; Maxwell & Cole, 2007).

Moderated mediation analysis

The term *moderated mediation* is used to convey instances when the mechanism through which X

affects Y is moderated by a fourth variable W, such that the indirect effect is different at different values of W. When one or both of the component paths ($X \rightarrow M$, $M \rightarrow Y$) through the mediator is moderated, X's effect on Y is described as a *conditional indirect effect*. The simplest conceptualization of conditional indirect effects involves evaluating whether the moderating variable (W) influences the $X \rightarrow M$ relationship (*first stage* moderated mediation) or the $M \rightarrow Y$ relationships (*second stage moderated* mediation; Edwards & Lambert, 2007), see Figure 1. The first and second stages refer to the particular path (i.e., path *a* or *b*, respectively) of the indirect effect that is believed to be moderated by another variable. A first stage model is estimated with two equations:

$$M = i_M + a_1X + a_2W + a_3XW \tag{7}$$

$$Y = i_Y + c'X + bM \tag{8}$$

By including the moderator (W) and the product term (XW) in Equation 7, the effect of the independent variable on the mediator can vary as a function of the moderator. Similar to a general mediation model, the indirect effect of X on Y is calculated as the product of the effects of X on M and M on Y. However, in moderated mediation, the product term must also allow for the indirect effect to be conditional on W. By substituting Equation 7 into Equation 8, the first stage moderated mediation model can be estimated as

$$Y = i_Y + c'X + bi_M + a_1bX + a_2bW + a_3bXW \tag{9}$$

Here, X's effect on M is expressed as ($a_1 + a_3W$), and M's effect on Y is b. The conditional indirect effect (ω) of X on Y is then expressed as $\omega = (a_1 + a_3W)b$, which when rearranged is $\omega = a_1b + a_3bW$. Thus, the coefficient a_3b is the estimated effect of W on the indirect effect of X on Y through M.

In a second stage model, W moderates the path between the mediator and the dependent variable, see Figure 1D. This model is similarly estimated with two equations:

$$M = i_M + aX \tag{10}$$

$$Y = i_Y + c'X + b_1M + b_2W + b_3MW \tag{11}$$

Here, the moderator (W) and the product term (MW) are included in Equation 11, and Equations 10 and 11 can be rewritten as

$$Y = i_Y + c'X + b_1i_M + ab_1X + b_2W + b_3i_MW + ab_3XW \tag{12}$$

The conditional indirect effect (ω) of a second stage model is quantified as $\omega = a(b_1 + b_3W)$, where a is the effect of X on M, and ($b_1 + b_3W$) is the effect of M on Y. The expression $a(b_1 + b_3W)$ can be rewritten as $ab_1 + ab_3W$, where the coefficient ab_3 quantifies the effect of W on the indirect effect of X on Y through M.

Hypothesis testing to determine whether the a_3b (or ab_3) coefficient, known as the *index of moderated mediation*, is statistically different from zero can be carried out through bootstrap confidence interval evaluations (Hayes, 2015). A confidence interval that does not contain zero is evidence that the indirect effect is moderated. The index approach to testing moderated mediation is useful because it relies on only one inferential test and directly assesses the statistical significance of the relationship between the moderator and the indirect effect. An alternative method, referred to as the *piecemeal approach* (Edwards & Lambert, 2007), involves separately testing moderation and mediation and then jointly interpreting the results. While the piecemeal approach should not be used in place of the index test, it can be useful to conduct separate analyses of moderation and mediation prior to or following the integrated method in order to better understand the nature of the conditional indirect effect (Hayes, 2018a). The index approach is well suited for instances in which the indirect effect is a linear function of W, as in a simple first or second stage model. However, it cannot be used when X's effect on M and M's effect on Y are both moderated by the same continuous variable. In this case, the indirect effect takes on a non-linear, quadratic, form as a function of W (Edwards & Lambert, 2007; Hayes, 2015).

A statistically significant index of moderated mediation provides evidence that the indirect effect is conditional on values of the moderator; however, this does not imply that the indirect effect is statistically different from zero at all points of W. In order to ascertain at which points of W the indirect effect is significant, formal testing of the indirect effect at various values of W is required. When the moderator is categorical, the indirect effect is simply tested at the coded values of W. For continuous variables, the choice of W values at which to test the indirect effect is less straightforward. Researchers often rely on commonly used conventions to select points that represent low, medium, and high values on the moderator. One convention is to plot the mean and one standard deviation both above and below the mean. Another common choice is to select values representing various percentiles of the variable's distribution, such as the 25th, 50th, and 75th percentiles. In other situations, the choice of values may be guided by theory, such that specific values are most relevant to the research question or clinical practice. Once values of the moderator are selected, the indirect effect is estimated and tested at each selected value of W with the construction of confidence intervals.

After estimating a statistically significant index of moderated mediation, practical significance is assessed with measures of effect size. A common method for obtaining effect sizes is to standardize the direct and indirect effects, thereby expressing the effects in terms of standard deviations. When X and Y are both continuous, the completely standardized direct and indirect effects quantify the amount of standard deviation change in Y that is associated with a one standard deviation increase in X. In moderated mediation analysis, standardized effect size measures are obtained by standardizing the conditional indirect effects of X on Y at various values of the moderator. For example, in a second-stage model where W moderates the path between M and Y, the completely standardized conditional indirect effect is expressed as

$$\omega_{\mathrm{cs}} = [s_X(ab_1 + ab_3W)]/s_Y \qquad (13)$$

where s_X and s_Y are the standard deviations of X and Y. When X is dichotomous (e.g., representing group membership) and Y is continuous, standardization by the scale of only Y provides partially standardized direct and indirect effects. The partially standardized conditional indirect effect in a second-stage model is

$$\omega_{\mathrm{ps}} = (ab_1 + ab_3W)/s_Y \qquad (14)$$

For mediation models without moderation, standardized effect sizes have been shown to perform better than other effect size measures in terms of bias, power and Type I error rates (Miočević et al., 2018). In addition, Lachowicz et al. (2018) recently proposed a novel effect size measure for quantifying the explained variance in mediation models. Further research is needed to develop effect size measures for moderated mediation analysis.

The review of moderated mediation analysis presented in this paper is relevant for estimating conditional indirect effects using ordinary least squares (OLS) regression. Moderated mediation can be implemented in many statistical software programs (e.g., Mplus, R, SAS, SPSS, Stata) through specification of a number of regression equations. However, the PROCESS macro (Hayes, 2018a) is specifically tailored for conducting regression-based moderated mediation analyses in SPSS and SAS with minimal programming required. With a single line of syntax, the PROCESS macro estimates all model coefficients, standard errors, test statistics, and bootstrap confidence intervals, including those for the index of moderated mediation. Alternatively, conditional indirect effects can be estimated using a structural equation modelling (SEM) framework. Rather than estimate each equation separately as is done in OLS regression, SEM estimates all model parameters simultaneously, using an iterative process such as maximum likelihood. Moreover, SEM allows for the analysis of latent variable models, whereas OLS regression can accommodate only observed variables.

Illustration

While examples of moderation and mediation are abundant in social science research, fewer studies integrate the two analyses in a single model. We illustrate the usefulness of moderated mediation analysis to education research in the context of evaluating whether school-wide student engagement mediates the association between the prevalence of teasing and bullying (PTB) and school-level performance on a standardized reading exam, and whether this association is moderated by supportive school climate. Prior research at the middle-school level has demonstrated that student engagement partially mediates the association between perceptions of PTB and passing rates on standardized exams (Lacey et al., 2017). We extend this work by investigating whether the indirect effect of PTB through student engagement at the high-school level is contingent upon levels of supportive school climate. We hypothesize that support moderates the proposed indirect effect of PTB, such that when a school has a less supportive climate, PTB has a stronger negative association with standardized exam performance through student engagement. To control for school composition effects, two school demographic variables were included as covariates: the percentage of racial minority students and the percentage of students eligible for free or reduced price meals (FRPM).

Figure 2 provides a graphic representation of our path model. PTB was the focal predictor (*X*), engagement was the mediator (*M*), support was the moderator (*W*), and reading achievement was the dependent variable (*Y*). The percentage of students eligible for FRPM and the percentage of racial minority students were included as covariates. As illustrated in Figure 2, we hypothesized a first-stage moderated mediation model, in which support was allowed to moderate the first-stage indirect path (*a*) through engagement. A direct effect of *X* on *Y* in mediation analysis can also be moderated, producing a *conditional direct effect*. To illustrate this, support was also allowed to moderate the direct path (*c*′) between PTB and reading achievement.

Although the present study uses school climate survey data from a state-wide sample of students in high schools, we estimate a series of single-level regression models using schools as the unit of analysis. We chose this modelling approach for two reasons. First, school climate is broadly defined as a multidimensional construct that encompasses the "quality and character of school life" and is "based on patterns of people's experiences of school life" (Cohen et al., 2009, p. 182). By this definition, school climate is a characteristic of the school, not individual students. Therefore, in school climate research, student ratings of the school environment are aggregated to the school level, reflecting the collective perspective of students (Lüdtke et al., 2009; Marsh et al., 2012). Accordingly, in the present study, the substantive predictors are conceptualized as school-level constructs that represent students' shared perceptions of the school. Second, in order to present an introductory tutorial of moderated mediation analysis, we restrict our analysis to the school level, using single-level models with manifest variables. Methods for assessing multilevel moderated mediation with latent variable interactions have only recently been developed (Zyphur et al., 2019) and are beyond the scope of this article.

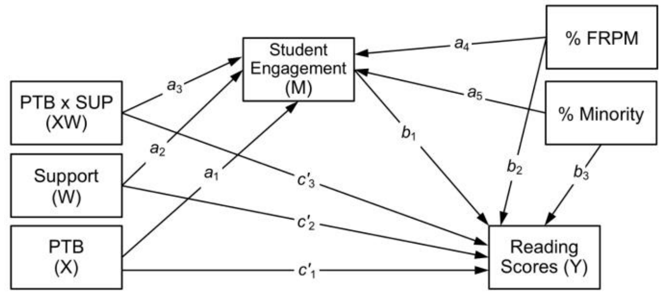

Figure 2. Moderated mediation model of associations between prevalence of teasing and bullying and reading achievement scores, with student engagement as the mediator, and support as the moderator.

Methods

Sample

Data came from the 2018 Virginia Secondary School Climate Survey. The sample consisted of 318 public high schools. The total school enrollment for Grades 9 to 12 ranged between 58 and 3,963 students (*M* = 1,214.30, *SD* = 720.76). Across schools, the percentage of students eligible for free or reduced-priced meals varied between 2.0% and 100% (*M* = 42.8%, *SD* = 22.8%). The percentage of racial minority students in each school ranged from 0.0% to 99.2% (*M* = 42.0%, *SD* = 26.6%).

Procedure

The survey was administered to students in grades 9-12 as part of the state's mandatory annual School Safety Audit. The participation rate was 99.4% for schools and 82.0% for students. Parental passive consent and student assent were obtained for all participants. The survey was administered anonymously through a secure online platform. Students completed the survey during normal school hours under the supervision of school staff. Of the 324 schools eligible for participation in the survey, the analytic sample consisted of 318 schools that completed the survey. Alternative schools for special populations, such as students transitioning from juvenile correctional centers, were excluded from the analytic sample.

Measures

The 108-item survey assessed student perceptions of school climate and safety conditions. Three survey scales relevant to this study included the prevalence of teasing and bullying, student engagement, and support. Scale items were measured using a 4-point response format (1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, 4 = *strongly agree*). To assess the reliability of the aggregated student ratings of each scale, we used the intraclass correlations *ICC*(1) and *ICC*(2) (Lüdtke et al., 2009)[1]. The *ICC*(1) is an indicator of the amount of variation in a variable that can be attributed to differences between clusters (i.e., schools). The *ICC*(2) estimates the reliability of cluster-mean ratings, where values closer to 1 indicate greater reliability.

Prevalence of teasing and bullying. PTB was measured with five items that assessed student perceptions of the extent of teasing and bullying at school. Previous studies using the PTB scale have found good overall model fit for the factor structure in samples of high school students (Bandyopadhyay et al., 2009; Klein et al., 2012). In contrast to other measures in this study, higher PTB scores are reflective of more adverse conditions (i.e., higher levels of teasing and bullying). Cronbach's alpha was .86 in the current sample. The *ICC*(1) was .08, indicating that 8% of the total variation in student ratings of PTB was attributable to the nesting of students within schools. The *ICC*(2) was .98, indicating a high degree of reliability of the school-mean ratings.

Student engagement. The student engagement scale consisted of six items that assessed both cognitive (e.g., Getting good grades is very important to me) and affective (e.g., I feel like I belong at this school) aspects of engagement that combine into a single measure of student engagement (Konold et al., 2014). The scale was adapted from the Commitment to School scale (Thornberry et al., 1991). In the current study, Cronbach's alpha was .77, *ICC*(1) was .06, and *ICC*(2) was .98.

Support. Student perceptions of their teachers as being supportive was measured with an eight-item scale that demonstrated good psychometric properties when evaluated through multilevel confirmatory factor models (Konold et al., 2014). Questions asked students to rate how strongly they agreed or disagreed that teachers at their school care about students (e.g., Most teachers listen to what students have to say; If I tell a teacher about a problem I am having, the teacher will do something to help). Cronbach's alpha was .87 in this sample. The *ICC*(1) was .05, and *ICC*(2) was .97.

Reading achievement. Reading achievement was measured using school-mean scaled scores on the Virginia Standards of Learning (SOL) End of Course (EOC) English Reading exam. SOL exams assess student proficiency in meeting the state's minimum expectations for end-of-year competency in various subjects. School-level SOL data were obtained from the Virginia Department of Education. We chose to measure academic achievement using 11th-grade reading scores because the majority of Virginia public high school students take the English Reading exam at the end of grade 11.

Analytic plan

To evaluate whether student engagement mediates the association between PTB and reading scores, and whether the indirect effect is further conditional on levels of support, a moderated mediation model was tested using the PROCESS macro (V3.3; Hayes, 2018a) for SPSS. PROCESS is preprogrammed with 92 models and numerous options for model specification. The present study used Model 8 that specifies a first-stage moderated mediation model in which W is allowed to moderate the direct path from X to Y and the first-stage indirect path from X to M. Support and PTB were mean centered prior to creating product terms, and the index of moderated mediation was tested with a 95% bias-corrected bootstrap confidence interval based on 10,000 replications. Moderation was further probed by estimating and plotting the conditional direct and indirect effects of PTB at values of support corresponding to the 16th, 50th, and 84th percentile points. These three points represented low (W = 2.94), moderate (W = 3.07), and high (W = 3.19) values of

[1]The $ICC(1) = \tau^2 / [\tau^2 + \sigma^2]$, where τ^2 is the variance between clusters and σ^2 is the variance within clusters. The $ICC(2) = \frac{k \times ICC(1)}{1+(k-1) \times ICC(1)}$, where k is the average number of units within a cluster. In the present study, k = 671.

support in the current sample. Using PROCESS, hypothesis tests were conducted to determine whether the conditional indirect effect of PTB was statistically different from zero at these values of support. SPSS output from the PROCESS macro is provided in the Appendix.

Results

Descriptive statistics for all variables in the current analysis are presented in Table 1. As expected, PTB was negatively associated with student engagement ($r = –.60$, $p < .001$), support ($r = –.52$, $p < .001$), and reading scores ($r = –.36$, $p < .001$). In addition, engagement was positively associated with support ($r = .77$, $p < .001$) and reading scores ($r = .44$, $p < .001$). Finally, support was positively associated with reading scores ($r = .15$, $p < .01$).

Results of the moderated mediation analysis are provided in Table 2. The direct association between PTB and readings scores was found to be moderated by support ($c'_3 = 36.69$, $p = .01$). The association between PTB and the mediator (i.e., student engagement) was also conditional on levels of support ($a_3 = 0.74$, $p < .001$). In addition to estimating model parameters, it is helpful to visualize the results. Figure 3 presents a visual depiction of the interaction between *X* and *W* on *Y* (plot A) and on *M* (plot B). Plot A was constructed by estimating the simple effect of PTB on reading scores for low, moderate, and high values of support. Similarly, plot B was constructed by estimating the simple effect of PTB on student engagement for the three levels of support.

Table 1. Descriptive statistics and correlations among variables

	Mean	SD	Min	Max	2	3	4	5	6
1.Reading scores	440.04	12.93	371	497	–.29**	–.72**	–.36**	.44**	.15**
2.% Minority	41.95	26.61	0.00	99.18	—	.34**	–.07	–.20**	–.29**
3. % FRPM	42.75	22.82	2.00	100		—	.35**	–.34**	–.13*
4. PTB	2.43	0.22	1.72	2.96			—	–.61**	–.52**
5. Engagement	3.10	0.14	2.58	3.50				—	.77**
6. Support	3.07	0.13	2.68	3.48					—

Note. *p < .05; **p < .01

Table 2. Moderated mediation results

	Student Engagement (*M*)		Reading Scores (*Y*)	
Predictor	Coeff. (*SE*)		Coeff. (*SE*)	
Control variables				
% FRPM	–0.10 (0.02)**	a_4	–29.44 (2.57)**	b_2
% Minority	0.01 (0.02)	a_5	–7.55 (2.29)**	b_3
Independent variables				
PTB (*X*)	–0.15 (0.03)**	a_1	–8.15 (3.07)**	c'_1
Support (*W*)	0.71 (0.04)**	a_2	–31.79 (6.47)**	c'_2
Student engagement (*M*)	—		34.80 (6.17)**	b_1
Interaction term				
PTB X Support	0.74 (0.13)**	a_3	36.69 (14.56)*	c'_3
R^2	0.72		0.60	
Conditional indirect effects	Coeff. *(SE)*		*95% CI*	
Low support	–8.66 (2.37)*		–13.25, –4.06	
Moderate support	–5.37 (1.63)*		–8.70, –2.38	
High support	–2.30 (1.57)		–5.63, 0.49	
Index of moderated mediation	25.66 (9.30)*		6.87, 43.16	

Note. Regression coefficients are unstandardized; standard errors are in parentheses. Bootstrap sample size = 10,000. CI, confidence interval. Path labels (e.g., a1) correspond to Figure 2. *p < .05; **p < .01.

As shown in Figure 3 plot A, PTB was negatively associated with reading scores for all levels of support, such that as PTB increased, reading scores decreased. However, as depicted by the steepness of the slopes, the negative relation between PTB and reading scores was largest in magnitude among schools characterized by low levels of support. Likewise, Figure 3 plot B illustrates that support moderated the association between PTB and student engagement, such that the magnitude of the association was strongest for schools with low support. The magnitude of the indirect effect was more negative among schools with relatively low levels of perceived support. As support decreased, PTB was associated with less student engagement, which, in turn, was associated with lower reading achievement.

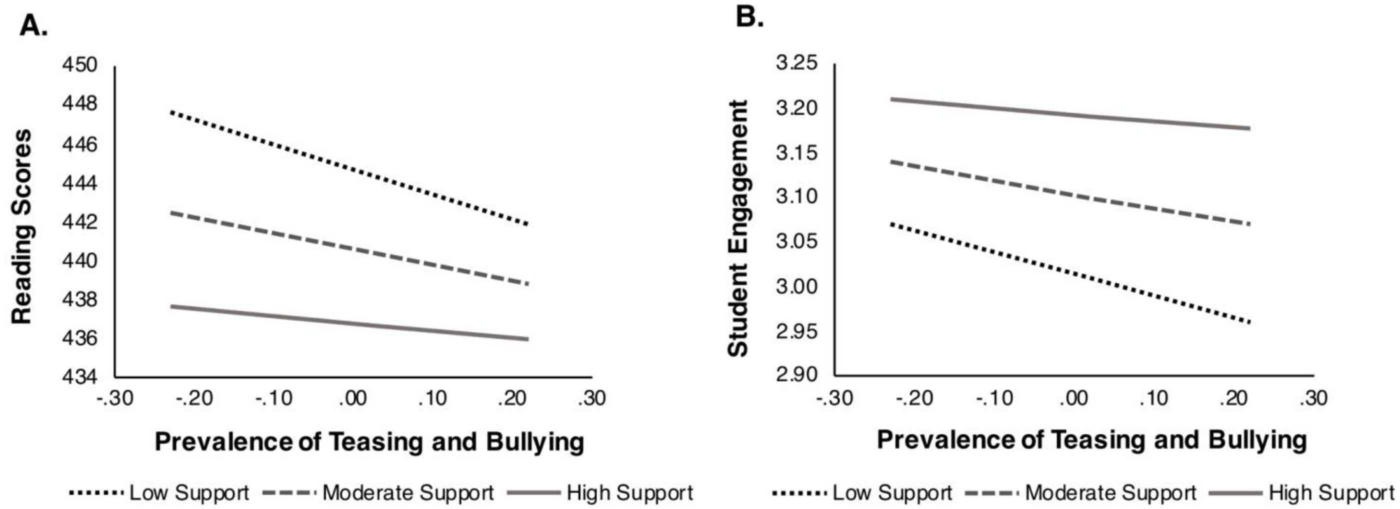

Figure 3. Conditional direct effects of PTB on reading scores (plot A) and student engagement (plot B).

Most notably, a formal test of moderated mediation based on the index term (Hayes, 2015) revealed that support moderated the indirect effect of PTB on reading scores (a_3b_1 = 25.66, 95% CI = 6.69, 43.40). Further hypothesis tests were conducted to determine whether the conditional indirect effect ($\omega = a_1b_1 + a_3b_1W$) was statistically significant at values corresponding to low (W = 2.94), moderate (W = 3.07), and high (W = 3.19) values of support as noted above. This was accomplished through PROCESS as the default, in that PROCESS automatically generates these conditional indirect effects at moderator values corresponding to the 16th, 50th, and 84th percentile points in the sample data. Results revealed that student engagement mediated the association between PTB and reading scores for schools with low support (ω_{Low} = –8.66, CI = –13.30, –4.09) and moderate support (ω_{Moderate} = –5.37, CI = –8.74, –2.40), but there was no evidence of an indirect effect for schools with high levels of support (ω_{High} = –3.77, CI = –9.89, 2.35). The

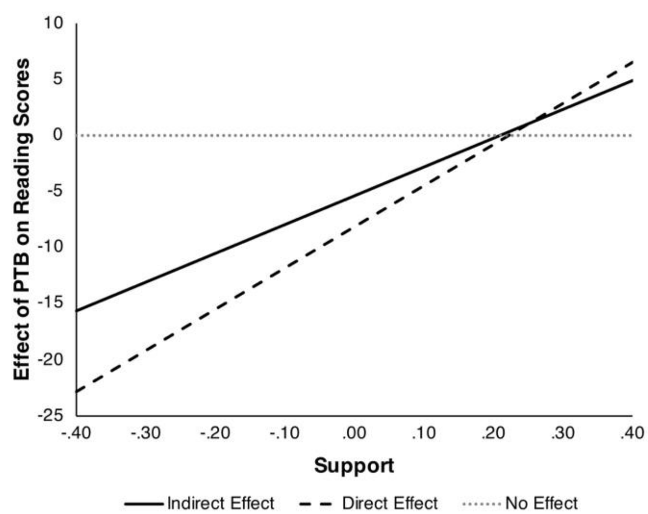

Figure 4. Direct and indirect effects of PTB on reading scores conditional on support.

The conditional direct and indirect effects of PTB on reading scores are depicted in Figure 4. The graph was constructed by plotting the estimated direct and indirect effects as functions of support. The horizontal axis shows the support scale centered around the sample mean of 3.07. The conditional direct effect is $c'_1 + c'_3W$, where c'_1 indicates the level of the direct effect at $W = 0$, and c'_3 is the slope. The conditional indirect effect is $a_1b_1 + a_3b_1W$, where a_1b_1 indicates the level of the indirect effect when $W = 0$, and a_3b_1 is the slope. Figure 4 shows that the indirect effect of PTB through engagement is stronger in magnitude (i.e., further away from zero) for schools with lower levels of support. The same trend is depicted for the conditional direct effect of PTB. Moreover, the graph illustrates that as support increases, both the direct effect and indirect effect diminish, meaning the effects approach zero.

Discussion

Both moderation and mediation allow researchers to address questions concerning contingencies and mechanisms that can better reveal the complexities of how a set of variables is interrelated. In recent years, applications of statistical mediation have become more prevalent in social science research for testing assumptions about why or how an independent variable is associated with an outcome of interest. However, mediation may not hold in all conditions or for all groups of people. In this paper, we reviewed and illustrated how moderated mediation analysis can be used to test whether an indirect effect is conditional on values of a proposed moderating variable. Despite its advantages for modeling complex relationships among variables, moderated mediation is under-utilized in the substantive literatures. Instead, researchers typically analyze interactions and mechanisms separately, or rely on other outdated methods for testing moderated mediation.

In our applied example, we found that student engagement mediated associations between PTB and readings scores, and this indirect effect differed among schools with varying degrees of supportive school climate. We used the index of moderated mediation (Hayes, 2015) to formally test our hypothesis. Unfortunately, some applied researchers continue to evaluate the presence of moderated mediation using subgroup analysis, in which mediation analyses are conducted separately for different groups of the sample based on values of the moderator. For instance, using our example, subgroup analysis would involve creating a priori subsamples of schools based on levels of support (e.g., low, moderate, and high), estimating indirect effects separately for each group, and then evaluating moderated mediation based on a descriptive comparison of the indirect effects. This approach is problematic because it (1) requires the categorization of a continuous moderator, which results in loss of information, and (2) does not formally test whether differences between indirect effects across subgroups are statistically significant (Hayes, 2018a).

Alternatively, other researchers more appropriately use the entire sample to estimate the indirect effect, but evaluate moderated mediation based solely on the conditional direct effect of X on M in a first-stage model, or M on Y in a second-stage model. In this case, no formal test of the product term, or index of moderated mediation, is conducted. The problem here is that the presence of a statistically significant interaction between two regressors on a mediator (e.g., path *a*3, in Figure 2) is not sufficient evidence of a conditional indirect effect (Hayes, 2015). In our example, although support moderated the association between PTB and engagement, we would have concluded that the indirect effect was not moderated if the index term was not statistically significant.

Substantively, we illustrated the application of moderated mediation analysis within the context of school climate research. Given that school climate is widely considered a key factor in promoting positive student outcomes, it is important to understand both the mechanisms underlying school climate effects as well as the conditions that may constrain these processes. Prior research has established that the prevalence of teasing and bullying is indirectly linked to academic achievement through student engagement in school (Lacey et al., 2017). The results presented here extend this work by demonstrating that the indirect effect of PTB through engagement is different for schools with different levels of supportive school climate. These findings re consistent with literature positing that supportive teacher-student relationships are important for fostering a school climate characterized by high student engagement (Pianta et al., 2012).

In answering our substantive research questions, a moderation focus alone would have allowed for examination of how the association between PTB and achievement was conditional on levels of supportive school climate. However, it would not have provided a test of the underlying process model linking PTB to achievement. Conversely, a focus on only the extent to which student engagement mediated the association between PTB and achievement would have tested the indirect effect, but a simple mediation analysis would not have revealed that the process model differed between schools with varying degrees of supportive climate. Moderated mediation analysis allowed for a simultaneous test of the mediating effect of engagement and the moderating effect of support.

Our application of moderated mediation within a linear regression framework was based on a relatively simple model with a single mediator and a single continuous moderator. Furthermore, we do not make inferences regarding causality. The methodological approaches discussed here can be extended to more complex models, such as those with multiple mediators (Preacher & Hayes, 2008), multiple moderators (Hayes, 2018b), multicategorical variables (Hayes & Preacher, 2014), latent variables (Lau & Cheung, 2012), longitudinal data (Cole & Maxwell, 2003), multilevel designs (Preacher et al., 2010), and Bayesian methods (Wang & Preacher, 2015). Readers interested in moderation and mediation within the context of causal inference are encouraged to see VanderWeele (2015). More generally, Hayes (2018a) provides a comprehensive treatment of regression-based methods and is an excellent resource for readers interested in learning more about the models discussed here.

The following limitations of our applied illustration should be kept in mind when conducting moderated mediation. First, the use of cross-sectional data limits interpretations to non-causal inferences. Researchers are encouraged to use longitudinal data, or prior state covariates, to establish temporal precedence and better inform understanding of the causal processes linking predictors (e.g., bullying) and outcomes (e.g., academic achievement). Second, although the measures of PTB, support, and engagement used in this illustration were based on Likert scales with four response categories; rating scales with more than four response categories have been shown to have better psychometric properties (i.e., less skewness and kurtosis) and are more likely to better approximate interval scales (Leung, 2011). Third, our moderated mediation model used schools as the unit of analysis by aggregating student ratings to the school level. Given clustered data structures, researchers are encouraged to consider recently developed methods for multilevel moderated mediation analysis (Zyphur et al., 2019) that account for measurement error and the sampling of students within schools.

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Appendix

Process macro documentation

```
process y=READING/x=PTB/m=ENGAGE/w=SUPPORT/cov=MINORITY FRPM/model=8/plot=1/
boot=10000/center=1/seed=1245.
Matrix
Run MATRIX procedure:
*************** PROCESS Procedure for SPSS Version 3.3 ******************
          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3
**************************************************************************
Model  : 8
    Y  : READING
    X  : PTB
    M  : ENGAGE
    W  : SUPPORT
Covariates:
 MINORITY FRPM
Sample
Size:  318
Custom
Seed:     1245
**************************************************************************
OUTCOME VARIABLE:
 ENGAGE
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .8463      .7162      .0057   157.4365     5.0000   312.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant     3.1472      .0108   291.6162      .0000     3.1260     3.1684
PTB          -.1542      .0267    -5.7655      .0000     -.2069     -.1016
SUPPORT       .7109      .0436    16.2976      .0000      .6251      .7968
Int_1         .7373      .1268     5.8141      .0000      .4878      .9868
MINORITY      .0059      .0210      .2822      .7779     -.0354      .0472
FRPM         -.1016      .0229    -4.4385      .0000     -.1467     -.0566
Product terms key:
 Int_1    :        PTB      x        SUPPORT
Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0308    33.8041     1.0000   312.0000      .0000
----------
    Focal predict: PTB      (X)
          Mod var: SUPPORT  (W)
Conditional effects of the focal predictor at values of the moderator(s):
    SUPPORT     Effect         se          t          p       LLCI       ULCI
     -.1285     -.2489      .0337    -7.3818      .0000     -.3153     -.1826
      .0000     -.1542      .0267    -5.7658      .0000     -.2069     -.1016
      .1195     -.0661      .0283    -2.3370      .0201     -.1217     -.0104
Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.
DATA LIST FREE/
   PTB        SUPPORT    ENGAGE     .
BEGIN DATA.
     -.2304     -.1285     3.0726
      .0213     -.1285     3.0099
      .2181     -.1285     2.9609
     -.2304      .0000     3.1421
      .0213      .0000     3.1033
      .2181      .0000     3.0729
     -.2304      .1195     3.2068
      .0213      .1195     3.1901
      .2181      .1195     3.1771
END DATA.
GRAPH/SCATTERPLOT=
 PTB       WITH     ENGAGE   BY       SUPPORT  .
**************************************************************************
OUTCOME VARIABLE:
```

```
 READING
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7774      .6044    67.4556    79.1775     6.0000   311.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant   348.9978    19.4619    17.9324      .0000   310.7042   387.2913
PTB         -8.1538     3.0679    -2.6578      .0083   -14.1902    -2.1173
ENGAGE      34.7987     6.1725     5.6377      .0000    22.6535    46.9440
SUPPORT    -31.7937     6.4712    -4.9131      .0000   -44.5267   -19.0608
Int_1       36.6864    14.5552     2.5205      .0122     8.0472    65.3256
MINORITY    -7.5531     2.2879    -3.3013      .0011   -12.0549    -3.0513
FRPM       -29.4441     2.5735   -11.4412      .0000   -34.5078   -24.3804
Product terms key:
 Int_1    :        PTB      x        SUPPORT
Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0081     6.3529     1.0000   311.0000      .0122
----------
    Focal predict: PTB      (X)
          Mod var: SUPPORT  (W)
Conditional effects of the focal predictor at values of the moderator(s):
    SUPPORT     Effect         se          t          p       LLCI       ULCI
     -.1285   -12.8670     3.9850    -3.2288      .0014   -20.7081    -5.0260
      .0000    -8.1542     3.0679    -2.6579      .0083   -14.1907    -2.1177
      .1195    -3.7684     3.1103    -1.2116      .2266    -9.8883     2.3515
Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.
DATA LIST FREE/
   PTB        SUPPORT    READING    .
BEGIN DATA.
     -.2304     -.1285   447.6300
      .0213     -.1285   444.3918
      .2181     -.1285   441.8595
     -.2304      .0000   442.4599
      .0213      .0000   440.4078
      .2181      .0000   438.8030
     -.2304      .1195   437.6487
      .0213      .1195   436.7003
      .2181      .1195   435.9587
END DATA.
GRAPH/SCATTERPLOT=
 PTB      WITH     READING  BY       SUPPORT  .
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************
Conditional direct effect(s) of X on Y:
    SUPPORT     Effect         se          t          p       LLCI       ULCI
     -.1285   -12.8670     3.9850    -3.2288      .0014   -20.7081    -5.0260
      .0000    -8.1542     3.0679    -2.6579      .0083   -14.1907    -2.1177
      .1195    -3.7684     3.1103    -1.2116      .2266    -9.8883     2.3515
Conditional indirect effects of X on Y:
INDIRECT EFFECT:
 PTB        ->    ENGAGE      ->    READING
    SUPPORT     Effect     BootSE   BootLLCI   BootULCI
     -.1285    -8.6629     2.3673   -13.2484    -4.0573
      .0000    -5.3671     1.6272    -8.7016    -2.3828
      .1195    -2.3000     1.5687    -5.6288      .4869
      Index of moderated mediation:
           Index     BootSE   BootLLCI   BootULCI
SUPPORT    25.6560     9.2996     6.8690    43.1603
---
********************** ANALYSIS NOTES AND ERRORS ************************
Level of confidence for all confidence intervals in output: 95.0000
Number of bootstrap samples for percentile bootstrap confidence intervals: 10000
W values in conditional tables are the 16th, 50th, and 84th percentiles.
NOTE: The following variables were mean centered prior to analysis: SUPPORT  PTB
------ END MATRIX -----
```