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Christopher J. Hopwood

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RESEARCH METHODS ARTICLE

Moderation and Mediation in Structural Equation Modeling: Applications for Early Intervention Research

CHRISTOPHER J. HOPWOOD
Texas A&M University

Second-generation early intervention research typically involves the specification of multivariate relations between interventions, outcomes, and other variables. Moderation and mediation involve variables or sets of variables that influence relations between interventions and outcomes. Following the framework of Baron and Kenny's (1986) seminal paper, this paper differentiates moderation and mediation conceptually and methodologically. Four cases of moderation defined by the scale of predictor and moderator variable scales are described, and several design and statistical issues associated with testing mediation are discussed. Use of structural equation modeling is proposed to address some of the difficulties in testing moderation and mediation effects. A hypothetical early intervention data set is used to discuss and demonstrate the use of structural equation modeling for examining moderation and mediation.

Researchers in early intervention increasingly are moving beyond asking global efficacy or effectiveness questions to asking questions that permit systematic examination of which interventions are most effective for which children and families under what circumstances. Guralnick (1993) has distinguished these as first- and second-generation research questions. First-generation research involved demonstrating the global efficacy or effectiveness of early interventions. Second-generation research involves the specification of child, family, and intervention characteristics that interact to optimize particular treatments under certain conditions.

Statistically, first- and second-generation research can be distinguished by the types of tested effects and, more specifically, the number and types of variables involved in those tests. In first-generation research, the main effect of one variable on another is tested. For example, Morrison, Sainato, Benchaaban, and Endo (2002) demonstrated an intervention that increased independent play among preschoolers with autism. In the language of research design, an intervention demonstrated a main effect on an outcome.

In second-generation research, the conditions under which main effect(s) operate between two variables are specified. These conditions represent third variables in research designs. For example, it might be that family support (third variable) enhances the effect of the intervention proposed by Morrison et al. (2002) on independent play. Or, it might be that different interventions are needed for children with autistic spectrum disorders than for children with oppositional/conduct disorders, and still different interventions for children with expressive or receptive speech delays.

The purpose of this article is to specify two classes of third variables that might be used to address second-generation research questions, moderators and mediators, and to demonstrate their use and applications in early intervention research. Traditional approaches to moderation and mediation will be discussed, followed by a description of the use of structural equation modeling for examining these models.

Moderation and Mediation Defined

Moderation involves a third variable (or set of variables) that acts as a controlling condition for the effects of variables (or sets of variables) on other variables (or sets of variables). To maintain clarity, the present paper will be limited to cases in which one "third" variable influences the effects of one intervention on one outcome. Unless otherwise noted, it is assumed that multivariate function scores[1] are subject to the same influences and defined by the same properties as univariate scores.

Baron and Kenny (1986) described moderation as the function "which partitions a focal independent [predictor] variable in to subgroups that establish its domains of maximal effectiveness in regard to a given dependent variable" (p. 1173). In moderation, the effect of a predictor (*X*) on an outcome (*Y*) varies across levels of a moderator (*M*). For example, there might be a critical number of intervention sessions required to achieve desired effects. There also might be an upper threshold where there is no longer an increment to the effects, because the effect of the intervention has been fully achieved. Between these upper and lower limits, there might be a direct, linear effect of the number of exposures to an intervention on the magnitude of the outcome. In this case, the frequency of exposures to an intervention (*M*) ***moderates*** the effect of that intervention (*X*) on the outcome (*Y*).

Baron and Kenny (1986) defined mediation as the function "which represents the generative mechanism through which the

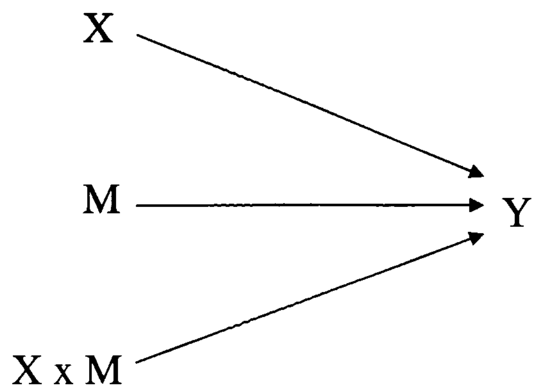

Figure 1.
Moderation.

focal independent [predictor] variable is able to influence the dependent variable of interest" (p. 1173). Mediation involves a third variable (*m*) that represents a temporal step between *X* and *Y* in a causal chain (see Figure 1). For example, the hypothesis that the intervention (*X*) described by Morrison et al. (2002) leads to more play time allocated within the daily routines of families of children with autism (*m*), which in turn leads to better play by children (*Y*), could be tested.

In addition to clarifying conceptual differences between moderators and mediators, Baron and Kenny also discussed strategic and statistical methods for testing moderation and mediation. They asserted that both classes of effects are best understood as multivariate (trivariate) models including *X*, *Y* and *M*/*m* variables. Although they clarified the current state-of-the-art in testing moderation and mediation effects, they also noted several problems with the methods proposed. Statistical methods and issues associated with using these methods for examining moderation and mediation are discussed.

Moderation

Baron and Kenny discussed moderation across four cases depending on the scale (quantitative or qualitative) of the *X* and *M* variables. Qualitative variables are treated as categories in research design (e.g., between subjects groups defined by participant gender), whereas quantitative variables are

[1] Multivariate function scores estimate the effect of a set of variables on an outcome, thus allowing the researcher to treat multiple variables as a single factor in statistical designs.

treated as dimensions (e.g., scores on a measure of a psychological construct). The case of a *qualitative X and M* consists of an interaction effect between X and M predicting Y in a 2×2 ANOVA. Given a statistically significant interaction and an M variable with more than two levels, simple effects of X can be tested across levels of M. For example, developmental level might moderate the effect of general intelligence on the ability to abstract. Children who are 1 year of age might be unable to abstract whether they are intelligent or not, whereas 3-year-olds might be able to perform simple abstractions, and 5-year-olds more complicated abstractions, depending on their level of intelligence.

The effect of a *quantitative* (dimensional) X variable on Y also might differ across levels of a *qualitative M*. A common example involves any effects that differ for boys and girls. As Baron and Kenny (1986) noted, the traditional way to test such a hypothesis is to compare the effect of X on Y for boys and girls. If these values (in the bivariate case the correlations) differ significantly, moderation is thought to be operating; however, Baron and Kenny pointed out several problems with this method. First, if the variance in X is unequal across levels of M, differences in the effect of X on Y across levels of M might be due to varying range in X across levels of M rather than a true moderator effect. For example, the effect of an intervention involving playing with gender-specific toys (e.g., dolls) on verbal expression might be larger among girls than boys. If this were demonstrated, however, it would not be clear if it were due to range restriction related to the fact that boys tended not to play with the dolls or a true moderation of intervention by gender. Second, if measurement error in predictor variable scores differs across levels of M, coefficients between X and Y will differ across levels of M. Unlike correlation coefficients, unstandardized regression coefficients (i.e., "b" weights) are not influenced by the variance of X across levels of M or measurement error in Y, and Baron and Kenny recommend their use in this case. If measurement error differs in Y across levels of M, biased estimates can result.

A third type of moderation involves *qualitative X and quantitative M* variables. One hypothetical example of this type of moderation is that family income might moderate the effect of ethnicity on education-esteem. It might be hypothesized that Asians tend to value education no matter what their income but that wealthy Anglos value education more than poor Anglos. If this were true, it could be further hypothesized that early interventions targeted at increasing children's preparedness for school might be generally effective for Asians and wealthy Anglos, because they would be supported by the family system, but would be less effective for poor Anglos, whose families might not actively support the intervention.

Baron and Kenny (1986) pointed out that the relation between M and the effect of X on Y can be modeled as a linear, curvilinear, or step function. In a linear function, the effect of X on Y is constant across all levels of M. In a curvilinear function, the effect maximizes at a certain level of M, and minimizes as the value of M differs from that optimal value. In a step function, the effect of X on Y is not present above and below certain critical thresholds on M, but is linear between those thresholds. Baron and Kenny also provided suggestions for what to do depending on the anticipated nature of this effect. The linear case is the simplest. In this case, M, X, and the product of M and X represent a regression model predicting Y. As in the second case described previously, it is important that measurement error in M is equal across levels of X. Curvilinear functions can be tested by including a quadratic term in the regression model previously described: $X + M + XM + M^2 + XM^2 = Y$. In this case, the penultimate term (XM^2) represents curvilinear moderation. For step functions, M can be dichotomized at the step, and treated as a qualitative variable. Moderation is then tested as the interaction effect in ANOVA.

The fourth case of moderation is very similar to the third, although it involves *quantitative X and M* variables. For example, the effect of an intervention to augment sharing behaviors during play might be moderated by the familiarity of the children, as defined by the number of previous periods in which they had played together. Similar to qualitative X and quantitative M, if a step function is anticipated to describe the moderation effect, M can be dichotomized and the second case of moderation (qualitative M, quantitative X) can be tested. This might be the case if it is believed that the intervention will not work if there have been no play periods previously, but will work equally well for children who had played previously, no matter how many times. If the effect is thought to be linear or curvilinear, regression can be used, again with quadratic terms in the curvilinear case. This might be the case if it is anticipated that if the children had not played together enough (e.g., fewer than five times), they would not be familiar with each other and would be unaffected by the intervention, but if they had played together too much (e.g., more than 10 times), they would be too familiar to each other, and would be unaffected by the intervention.

Mediation

Mediation consists of a case in which a third variable is a pathway for the effect of a predictor on an outcome (see Kraemer, Wilson, Fairburn, and Agras, 2002, for a different interpretation). For example, an intervention for children with an autistic spectrum disorder would promote family use of the intervention at home, which would precipitate psychosocial improvement. Statistical mediation is shown in Figure 2. In the first, non-mediated case (i.e., bivariate correlation), the relation between X and Y equals c. In mediation, X leads to m, which leads to Y.

Baron and Kenny (1986) discussed four characteristics of mediation, indicated in Figure 2 by a, b, c, and c'. The first is a significant relation between X and Y (c), which would preclude interest in testing

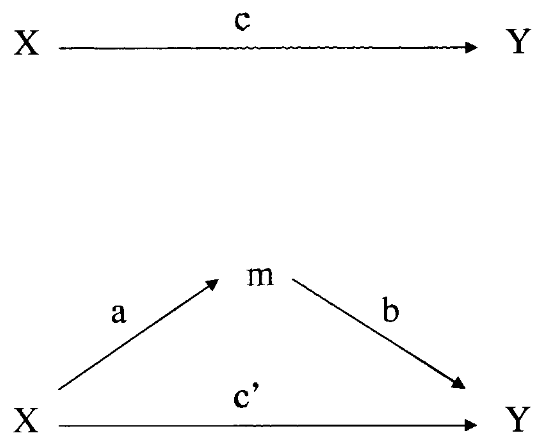

Figure 2.
Correlation and mediation.

mediation. This type of effect is what Guralnick (1993) referred to as first-generation research: early interventions promote better outcomes in young children. The second characteristic involves a relation between the predictor and mediator variables (a). In the previous example, early intervention by a practitioner would promote the use of that intervention by the family. The third involves an effect of the mediator on the outcome, after controlling for the predictor (b). To continue with the same example, use of the intervention by the family would precipitate the child's psychosocial improvement, independent of the effect of the intervention by the practitioner. Finally, c' represents the remaining effect of X on Y after accounting for m. In *full mediation*, this effect is zero, meaning that the effect of the practitioner's use of the intervention is no longer present once we account for the effect of the family's use of the intervention. That is, the function of the intervention was to teach the family how to use the intervention. Notably, this function would be misperceived in first–generation, early intervention research that did not specify the family's role. In *partial mediation*, the magnitude or direction of the effect might change, but it is still meaningful. This would be the case if both the practitioner's and the family's use of the intervention independently promoted improved psychosocial behavior in the child.

Baron and Kenny defined the *amount of mediation* as the reduction of the effect of the predictor on the outcome, or $c - c'$. They also noted that it can be mathematically demonstrated that $ab = c - c'$ when all variables are observed, and that this is approximately so when variables are latent.

Several methods for computing a *standard error* also have been developed for the mediation effect. Goodman (1960) developed the first, sample-based method, in which the standard error of ab $(S_{ab}) = (b^2S_a{}^2 + a^2S_b{}^2 - S_a{}^2S_b{}^2)^{1/2}$. Baron and Kenny offered a population-based estimate, $S_{ab} = (b^2S_a{}^2 + a^2S_b{}^2 + S_a{}^2S_b{}^2)^{1/2}$, and Sobel (1982) developed an approximation without the final term, which is often very small, $S_{ab} = (b^2S_a{}^2 + a^2S_b{}^2)^{1/2}$. To test the mediation effect, ab/S_{ab} can be tested against a z distribution to test the null that ab is not different than zero.

Baron and Kenny noted several difficulties involved in testing mediation, including issues with the temporal relation between m and X versus m and Y, collinearity of m and X in predicting Y, the possibility that Y causes X rather than X causing Y, unreliable measurement of the mediator variable score, and the possibility that omitted variables relevant to the model have not been considered.

By definition, a and b independently must represent meaningful effects to test mediation. Because c constrains the possible effects of a and b ($ab \leq c$), a and b are dependent. The closer in time any two variables exist, the stronger the relation between those variables. Consider the example discussed previously, in which a practitioner's intervention predicated the use of that intervention by the family, resulting in improved psychosocial behavior by the child. If the practitioner's intervention occurs the day before the use of that intervention by the family is measured, but the child's behavior is measured 6 months thereafter, the likelihood is that X (clinician intervention) will be more strongly related to m (family's use of the intervention) than m will be related to Y (child's behavior). This is referred to as *proximal mediation*, which occurs when part of the effect a is related to the fact that m is temporally closer to X than it is to Y. It is not clear how much mediation is due to the experimental design and how much to the hypothesized effect. Conversely, in *distal mediation*, m is closer in time to Y than to X, and b might be overestimated and a underestimated. Distal mediation might occur if the practitioner's intervention occurs 2 weeks before the measurement of both the family's use of that intervention and the child's behavior.

Another issue in demonstrating mediation involves *multicollinearity*, or the effects of correlated predictor variables on estimates and hypothesis tests. Because a criterion for mediation involves a relation between X and m (a), multicollinearity is inherent in Baron and Kenny's model. To correct for this artifact, Baron and Kenny generally recommend large samples, and endorse the following equation to determine appropriate sample size: $N_{\text{observed}} = N_{\text{appropriate}}(1 - a^2)$.

Estimation of mediation in regression requires two assumptions that often are not met in experimental designs. First, scores on m are assumed to have been measured reliably. Biased estimates can occur due to *measurement error in mediator variable scores*. Given measurement error in m, the effect b cannot be totally controlled in estimating the effect c'. If mediation (ab) is positive, b is likely to be underestimated (and c' is overestimated). When mediation is negative, b is likely to be overestimated, and c' underestimated. A method to correct for the effect of measurement error in m scores is discussed below.

Second, the causal direction of m and Y or of X and Y might be mis-specified. The possibility that Y causes X can be addressed directly by making X an experimentally manipulated variable; however, m and Y are hypothesized to represent a causal path descending from X: they cannot be manipulated. A comparison of path coefficient b in two mediational models in which m and Y are reversed cannot be used to determine the direction of causality between m and Y, because path coefficients are likely to remain similar. Measuring m temporally prior to Y is one way to prevent the problem of *reverse* *cause*. Smith (1982) introduced a least-squares technique to test the direction of causality between m and Y. It involves, however, using two variables not associated with the mediational model, one of which correlates with m but not Y, and the other which correlates with Y but not m. In the absence of experimental assurances that X and m preceded Y, theory should guide decisions about the direction of causality.

A related experimental difficulty with mediation is the enduring possibility that the specified model has not accounted for one or more relevant variables. For example, path a or path b might be mediated by *unknown variable* Z. This, of course, cannot be addressed statistically, because in any case of mediation, the amount of mediation approximates the magnitude of the original bivariate correlation. Only theory can guide decisions about relevant variables, and researchers can never know with confidence that they have accounted for all relevant variables. Artifacts resulting from method effects, which have the potential to mediate a or b, can be addressed statistically. If m and Y (or m and X) are measured with similar methods (e.g. both self-report), the effect of m on Y might be overestimated. If m and Y are measured with dissimilar methods (e.g., self-report and biological indicator), the effect of m on Y might be underestimated.

Mixed Models

Two mixed models also can be specified (James & Brett, 1984; Muller, Judd, & Yzerbyt, 2005). *Mediated moderation* involves an interactive effect of two predictor variables (X_1 and X_2) on an outcome variable Y, and therefore also in a mediational process $X - m - Y$. For example, the effect of family education on the cognitive achievement might be mediated by family participation when there is programmatic support (e.g., regular training and support sessions) but not when there is no programmatic support (e.g., one education and support session without follow-up sessions) for such participation. That is, the mediational process family education – family participation – cognitive achievement is moderated by programmatic support. In this case, the interactive effect of X_1 and X_2 can be treated as X and the mediational model can be tested as described.

In *moderated mediation*, effect a or effect b is moderated by a fourth variable Z. This is related to the previous discussion regarding unknown variable Z, except that in moderated mediation Z is known. For example, the effect of family education on children's cognitive achievement might be mediated by family participation whether or not there is continued programmatic support, but the effect of family participation on cognitive achievement (b) might be stronger when there is programmatic support than when there is not, and thus the amount of mediation ($c - c'$) stronger with programmatic support than without. In the other case, the influence of family education on family support (a) might be stronger with programmatic support than without, again resulting in attenuated overall mediation ($c - c'$).

Using Structural Equation Modeling to Model Moderation and Mediation

Although this paper has used the framework provided by Baron and Kenny (1986) to discuss issues related to moderation and mediation, it is important to note that this is not the only perspective on these methods. For example, MacKinnon, Lockwood, Hoffman, West, and Sheets (2002) demonstrated that other methods can be more sensitive to the effects of third variables. Moderation and mediation also can be thought of from varying conceptual perspectives. For example, Kraemer et al. (2002) discussed mediation in a noncausal framework and specified further analyses to test the causality of predictors on mediators and mediators on outcomes.

It is not necessary that moderator and mediator models specify observed (measured) variables, and in many cases there are advantages to specifying latent variables. Latent variables, which are commonly used in applications such as factor analysis and structural equation modeling (SEM), represent scores that estimate the effect of several observed variables putatively measuring the same phenomenon. One advantage of using latent, as opposed to observed, variables is that the former tends to estimate the desired effect more reliably, because any variance associated with measurement error in a particular observed variable is unlikely to be shared across other observed variable(s), and thus will not contribute to the score on a shared latent variable. Because of this property, unreliability and method effects on models of moderation and mediation can be ameliorated through the use of SEM.

If measurement error differs in Y across levels of M in tests of moderation, biased estimates can result. Reliabilities that differ across levels of M can be modeled directly in SEM to attenuate this problem by reducing measurement error across all levels of M. In mediation, the use of SEM to model X, m, and Y as latent traits also attenuates concerns that method effects are confounded with substantive results.

Example Application Using Structural Equation Modeling

The use of SEM to test moderation and mediation is illustrated with hypothetical data from 20 subjects (e.g., children with special needs) using AMOS 3.62 (Arbuckle, 1997). It is important to note that, due to differing estimation methods and other factors, results might vary across software packages. In AMOS, structural models are drawn directly rather than inferred by specification of the variance/covariance matrices (although matrix specification is an option in AMOS), making it among the most user-friendly modeling interfaces. AMOS also is an attractive software package because of its direct compatibility with SPSS. Data can be read as correlation matrices with variable standard deviations, as covariance matrices, or as raw data. In the current example, raw data (see Table 1) were read into AMOS after the model had been specified with appropriate variable names. All measured variable scores ranged from 1 to 5.

In the example of moderation (see Figure 3), family support is thought to moderate the effect of social difficulties on preschool functioning. Social skills were modeled as a latent trait with two measured variables: parent and teacher report. The outcome variable, preschool functioning, was modeled as a latent trait with two measured variables: parent and teacher report of functioning[2]. Family support is modeled as a measured variable, which represents a composite rating provided by a research assistant who collected observational data in the home. The moderator variable is the interaction of social difficulties and family support. To obtain this value, a factor analysis with varimax rotation was conducted on parent and teacher reported social skills, and the standardized factor scores on the first (only) factor were saved. Next, family support was standardized. The product of these factor scores and standardized family support represents the interaction term.

To ensure the interpretability of path coefficients, overall model fit statistics need to be assessed before testing moderation effects. Model fit statistics compare the specified model to one without any constraints, meaning that all variables in the correlation matrix are free to relate to one another. Conversely, in SEM, model specification indicates that some variables should not relate to each other. For example, in the current model, it is specified that parent reports of social difficulties do not relate to parent reports of school functioning, except through the paths between the latent variables (i.e., no method effect was observed). Given the varying properties of fit statistics, the general convention is to cite the model chi-square and significance test, along with several other indices with the best properties as determined by empirical research (Hu & Bentler, 1998). In the present paper, the root mean square residual (RMR) and compara-

[2] Using similar methods across constructs often results in systematic method variance that can be modeled in SEM. For the purpose of clarity in this example, it is assumed that method variance is not an important factor.

Table 1
Raw Data Used in Structural Equation Model

SUB	PSD	TSD	PSF	TSF	FS	OI	TI	SDFAC	ZFS	SD_FS
1	1.00	2.00	5.00	4.00	2.00	1.00	2.00	−1.21	−.56	.57
2	2.00	1.00	5.00	5.00	1.00	1.00	2.00	−1.28	−1.35	1.47
3	3.00	3.00	4.00	5.00	4.00	3.00	4.00	.20	1.03	.17
4	3.00	2.00	4.00	4.00	3.00	3.00	3.00	−.32	.24	−.06
5	3.00	3.00	2.00	2.00	2.00	3.00	3.00	.20	−.56	−.09
6	4.00	4.00	5.00	4.00	5.00	3.00	4.00	1.16	1.83	1.79
7	4.00	4.00	1.00	2.00	2.00	4.00	3.00	1.16	−.56	−.54
8	5.00	4.00	4.00	3.00	4.00	3.00	4.00	1.61	1.03	1.40
9	1.00	2.00	3.00	4.00	2.00	2.00	2.00	−1.21	−.56	.57
10	2.00	2.00	5.00	3.00	3.00	2.00	2.00	−.77	.24	−.15
11	2.00	1.00	4.00	5.00	4.00	2.00	2.00	−1.28	1.03	−1.12
12	3.00	4.00	3.00	2.00	4.00	3.00	2.00	.71	1.03	.62
13	3.00	3.00	2.00	4.00	2.00	3.00	4.00	.20	−.56	−.09
14	3.00	3.00	2.00	2.00	1.00	3.00	3.00	.20	−1.35	−.22
15	4.00	4.00	2.00	2.00	2.00	4.00	4.00	1.16	−.56	−.54
16	5.00	4.00	1.00	2.00	1.00	3.00	4.00	1.61	−1.35	−1.83
17	1.00	2.00	5.00	4.00	2.00	2.00	2.00	−1.21	−.56	.57
18	3.00	2.00	3.00	2.00	3.00	3.00	2.00	−.32	.24	−.06
19	2.00	2.00	4.00	4.00	5.00	3.00	3.00	−.77	1.83	−1.18
20	3.00	3.00	2.00	1.00	2.00	4.00	5.00	.20	−.56	−.09

Note. SUB = Subject, PSD = parent-reported social difficulties, TSD = teacher-reported social difficulties, PSF = parent-reported school functioning, TSF = teacher-reported school functioning, FS = family support, OI = observer-reported isolating behavior, TI = teacher-reported isolating behavior, SDFAC = social difficulties factor score, ZFS = standardized family support score, SD_FS = SDFAC × ZFS.

tive fit index (CFI) were used. Each of these indices range from 0 to 1. With RMR, values close to 0 are preferable, and with CFI, values close to 1 indicate good fit. The model fit statistics for the moderator model ($\chi^2(8) = 3.678, p = .885$, RMR = 0.079, CFI = 1.000) indicate a good fit, meaning that little reliable score variance was lost in moving from a completely free variance covariance matrix to the more restricted, specified model.

In moderation, the paths between *X* (social difficulties) and *M* (family support) are

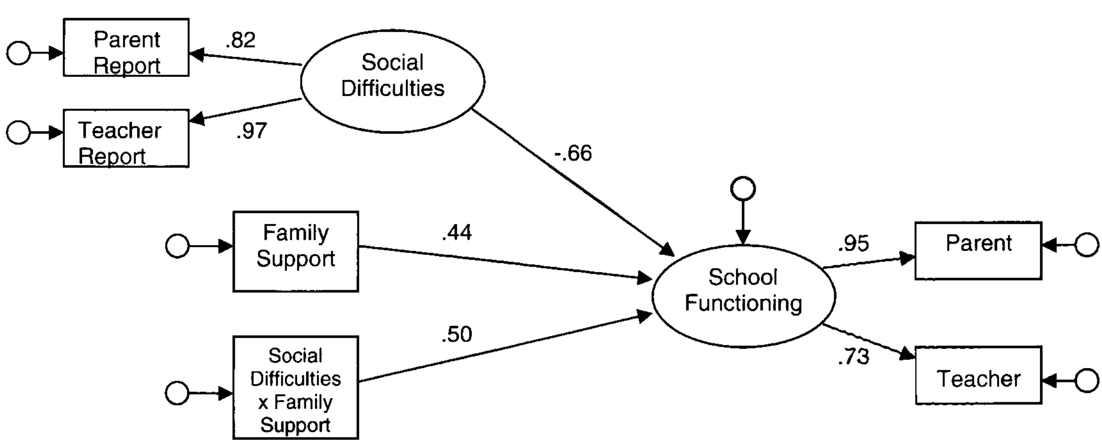

Figure 3.
Effect of social difficulties on school functioning moderated by family support.

Table 2
Critical Ratios for Latent Variables in Moderator, Correlation, and Mediatior Models.

Relation	Unstandardized path	Standard error	Critical ratio
	Moderation		
SD → SF	−0.88	0.21	−4.20
FS → SF	0.44	0.12	3.78
SDxFS → SF	0.71	0.17	4.33
	Correlation		
SD → SF	−0.83	0.32	−2.62
	Mediation		
SD → IB	0.66	0.21	3.13
SD → SF	−0.06	0.69	−0.08
IB → SF	−1.30	0.91	−1.44

Note. SD = social difficulties, FS = family support, SDxFS = interaction, IB = isolating behavior, SF = school functioning.

anticipated to be minimal, but the effect of their interaction (social difficulties x family support) on the *Y* (preschool functioning) is anticipated to be meaningful and statistically significant. Overall model fit in the absence of any paths relating social difficulties to family support means that these variables are mostly unrelated. The statistical significance of paths in structural models involves the critical ratio (C.R.), or the ratio of the unstandardized path to the standard error associated with that estimate. This is tested against a *z* distribution, with a value of 1.96 or greater indicating one-tailed significance at alpha = .05. In the hypothesized model, the C.R. for the interaction effect (4.332) is significantly different from zero at the .05 type-I error rate. Therefore, it is inferred that the frequency of support moderates the effect of social difficulties on school functioning. The critical ratios of the other paths also are statistically significant (i.e., > |1.96| see Table 2), suggesting important main effects of social difficulties and family support, in addition to their interactive effect.

The mediation example is shown in Figures 4 and 5. Figure 4 shows the effect of social difficulties on school functioning, both of which were previously described. The model fits, (χ^2 (1) = 0.474, p = 0.491, RMR = 0.020, CFI = 1.000), and the effect was statistically significant (see Table 2). Thus, Baron and Kenny's first criterion is met. The latter three must be demonstrated in the mediational model (Figure 5). The mediator variable, isolating behavior, is a latent factor with two measured variables, professional observer and teacher report of the frequency that children isolate when in the presence of peers. The overall model fits (χ^2 (6) = 6.151, p = .406, RMR = 0.067, CFI = 0.998). The paths from social difficulties to isolating

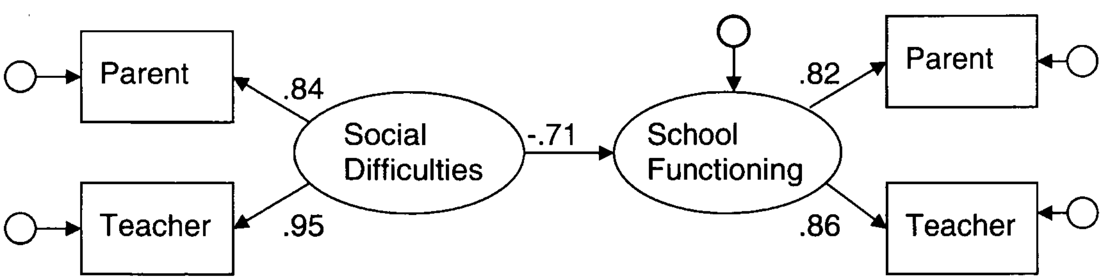

Figure 4.
Correlation of social difficulties and school functioning.

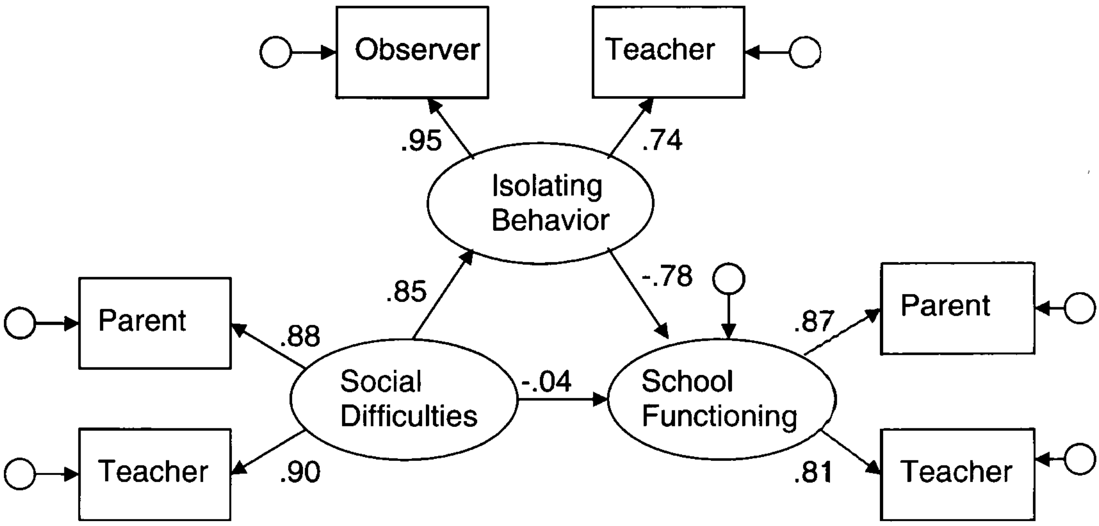

Figure 5.
Effect of social difficulties on school functioning mediated by isolating behavior.

behavior and from isolating behavior to school functioning are both strong, although only the critical ratio from social difficulties was statistically significant (see Table 2). If it is assumed that the failure to demonstrate statistical significance despite a large effect of isolating behavior on school functioning reflects a lack of power due to small sample size (necessary for ease of the current presentation), it can be inferred that Baron and Kenny criteria 2 and 3 were met.

The path from social difficulties to school functioning was near zero and not statistically significant (see Table 2), indicating full mediation of the effect of social difficulties on school functioning by isolating behavior. The amount of mediation was moderate ($c - c' = 0.68$, $ab = 0.66$). Before isolating behavior was specified as a mediator in the model, the effect of social difficulties on school functioning was meaningfully negative: the more social difficulties, the worse functioning. This would imply that social difficulties would be an appropriate target for early interventions (e.g., skills training); however, the mediational model paints a different picture. Social difficulties lead to isolating behavior, which leads to difficulties in school functioning. This implies that decreasing isolating behavior by encouraging social interaction, and not increasing social skills, might be a more appropriate target for early intervention. In this example, however, the data are hypothetical and for illustrative purposes only. No substantive conclusions should be drawn.

Conclusion

To help inform the conduct of second-generation early intervention research, moderation and mediation were discussed using the framework provided by Baron and Kenny (1986). Four types of moderation, differentiated by the scale of moderator and predictor variables, were described conceptually and statistically. A method was described for testing mediation that consists of methods to estimate the amount and statistical significance of mediation and several difficulties and potential solutions were discussed. Models that mix moderation and mediation also were discussed, and methods of testing them described. Finally, the advantages of using structural equation modeling to estimate moderational and mediational models were described and examples of both were offered using illustrative data relevant to early intervention research.

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Correspondence concerning this article should be addressed to **Christopher J. Hopwood,** Texas A & M University, Department of Psychology, College Station, TX 77843-4235. *E-mail: chopwood@tamu.edu*