Studying Aggression with Structural Equation Modeling

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This work was supported in part by grants from the NIH to the University of Kansas through the Mental Retardation and Developmental Disabilities Research Center (5 P30 HD002528), the Center for Biobehavioral Neurosciences in Communication Disorders (5 P30 DC005803), an NRSA fellowship to the first author (1 F32 MH072005), and a NFGRF grant (2301779) from the University of Kansas to the second author.

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Structural equation modeling (SEM) is one of the most powerful and flexible analytic tools for studying aggression and violent behavior. To illustrate its flexibility, we will briefly describe four applications of SEM that are particularly effective in the study of aggression: (a) modeling means, variances, and correlations in a single group, (b) examining group differences in means, variances, and correlations, (c) decomposing the multi-dimensionality of aggression, and (d) modeling the interdependent nature of aggression. While this list of topics is not exhaustive, it represents core uses that are relevant to the study of aggressive behavior. In addition, although we utilize examples from childhood and adolescence, the approaches we discuss are readily applicable to the study of violent behavior throughout the lifespan.

SEM is a latent variable technique. As such, one of its primary advantages is that constructs are represented without the presence of measurement error. In the social and behavioral sciences, manifest variable techniques such as ANOVA or regression are conducted in the presence of some degree of measurement error (unreliability) and, as a consequence, any estimates of effect size, be they differences in means or the degree of an association, are underestimated and are prone to bias because of sampling variability. As we will see, SEM is not limited to adjusting covariance relationships for unreliability, but they are also able to adjust mean-level estimates for measurement error. In addition to the error corrections of SEM, it also allows for nearly any system of linear equations to be simultaneously estimated, meaning that direct, indirect, mediated, and moderated relationships can be directly specified and estimated (Little, Card, Bovaird, & Crandall, in press).

In the process of specifying SEM models, the key is to measure multiple indicators for a given construct. In the following, we will discuss some of the choices that a researcher can make in estimating latent constructs with multiple indicators, and then we will discuss the various steps...
and procedures that are used in testing for similarities and differences in latent constructs.

**Modeling means, variances, and correlations in the study of aggression**

As mentioned, the analysis of latent variables with SEM offers several advantages over analysis of manifest variables using traditional techniques such as analysis of variance or regression. Advantages include greater ability to model complex multivariate relations (e.g., multiple dependent variables, indirect or mediated processes, interactive processes), estimating disattenuated parameter estimates (i.e., correcting for measurement error), and obtaining fit indices for these complex models (which allows for rigorous tests of competing models and specific hypotheses; see e.g., Kline, 2005; Little, Card, Slegers, & Ledford, in press).

Consider the hypothetical example depicted in Figure 1. The latent overt aggression construct is operationalized by three measured indicators (i.e., hits others, threatens others, and calls others nasty names) and the social aggression construct is operationalized by three measures (i.e., spreads rumors about others, excludes others from activities, and hurtfully manipulates relationships). Although constructs can be represented by as few as two indicators (i.e., measures representing a construct), there are numerous advantages to having three indicators for each construct. Most notable among these advantages is that the measurement of a given construct is locally 'just identified'. That is, once a scaling parameter has been fixed, the number of parameters needed to estimate the variance, loadings, and residuals associated with a given construct is equal to the number of unique variances and covariances among the indicators used to define the construct. With two indicators, the constructs parameters are not locally identified, which can lead to model identification problems unless additional constraints are placed on the estimates (e.g., a common constraint is to make the loadings of the two indicators be equal in magnitude; see Little, Lindenberger, & Nesselroade, 1999). If a research has four or more indicators of a construct, issues of identification are not in play, but the estimation of such constructs can be problematic as the number of indicators increases. On the other hand, if a researcher has a sufficient number of homogeneous indicators (items, scales, or measures) of a construct, combining indicators through parceling techniques can be used to represent constructs in a valid and unbiased manner (see Little, Cunningham, Shahar, & Widaman, 2002).

In order to model latent variables, it is necessary to set the scale of each latent variable in a model. In setting the scale of the variance / covariance structure, two common approaches are to either fix the variances of the latent variables at 1.0, or fix the loading of one arbitrarily selected indicator of each latent variable to be 1.0. Both of these approaches provide a sufficient condition to estimate the parameters of a given model, but the estimates are all in a metric that is generally arbitrary. An alternative approach that provides a less arbitrary metric is to constrain the factor loadings of the indicators to average 1.0 (for details see Little, Slegers, & Card, in press). Because of its less arbitrary metric, we view this latter approach as a particularly informative and useful method of setting the scale of the latent variables.

When modeling means (i.e., Mean and Covariance Structures, or MACS, analysis, see Little, 1997; Little, Card, Slegers, & Ledford, in press), the approaches to scale setting and identification of mean structures parallel those for scale setting on the variance/covariance parameters (and the method chosen to identify the mean structure should be the same as that chosen for the variance/covariance structure). Perhaps the most common approach is to fix all latent means in a reference group and estimate the latent means as relative differences across groups (an approach that is only useful in multi-group analyses; see next section). A second approach is to arbitrarily choose an indicator intercept to fix at zero. Both these methods also lead to an arbitrary metric for the mean structures of a model (see Little, Slegers, & Card, in press, for details). An alternative approach that yields less arbitrary estimates (which parallels the constraining method described above), is to simply constrain the means of all indicators of a
given construct to average 0 (see Little, Slegers, & Card, in press, for sample syntax and a comparison of the various methods).

The constraining method (also call effects-coded method; Little, Slegers, & Card in press) of scale setting has two critical advantages. A first advantage of this approach is that the latent means (i.e., $\alpha$’s) are estimated on the same metric as the manifest indicators. This property thereby allows comparisons of mean levels across constructs, not just across groups, and allows one to interpret the corresponding scale values (e.g., a latent mean of 4 where the indicators are all measured on a on a 1 to 7 scale means that respondents, on average, are at the midpoint of the scale). A second advantage of this method is that it allows one to examine the patterns of indicator means to determine which indicators have higher mean levels than others (e.g., in Figure 1, name calling may be more common than hitting others).

Returning to the hypothetical aggression example of Figure 1, our recommended approach to setting the latent scales would involve constraining the loadings ($\lambda$) of the hitting, threatening, and name calling indicators on overt aggression to average 1.0, and placing a similar constraint on the loadings of the three social aggression indicators. Assuming that all indicators are on a common metric (e.g., a 1 to 7 self-report scale, or percentages of peers nominating the individual), the latent construct metric would now be on this same metric. Then, if the intercepts (i.e., means) of these indicators are constrained such that the estimates sum to zero, the latent mean ($\alpha$) of the constructs is estimated on the same scale as its indicators (see Little, Slegers & Card, in press).

It is only with this constraining (effects-coded) approach that the means or the variances can be readily compared across these two forms of aggression (as well as across time or groups, as described below). To test whether the latent means or variances between overt and relational aggression differ, one would perform a nested-model comparison of an unrestricted model in which all latent means and variances are freely estimated with a restricted model in which the two means or the two variances are equated. Such nested-model comparisons utilize the resulting change in $\chi^2$ between the unrestricted and restricted models ($\Delta \chi^2 = \chi^2_{\text{restricted}} - \chi^2_{\text{unrestricted}}$, with $df = df_{\text{restricted}} - df_{\text{unrestricted}}$) to test the cross-construct differences in the means or variances. If the change is significant, then the equality constraint is not tenable, and the means or variances in overt and social aggression are different from one another.

As mentioned, comparisons of means in SEM are more powerful than such comparisons with manifest variables (i.e., traditional t-tests or analysis of variance) because the latent means are not attenuated by measurement error. Further, the resulting effect sizes will be disattenuated from the measurement error inherent in manifest variable analyses such as t-tests. Considering the example of overt and social aggression, the latent, disattenuated effect size for differences in the levels of these forms of aggression could be indexed by Cohen’s $d = (\alpha_{\text{overt}} - \alpha_{\text{social}}) / \sqrt{(\psi_{\text{overt}} + \psi_{\text{social}})}$. (note that the latent variances are represented in Figure 1 as the paths to the phantom variables, as described below, thus $\psi = \beta^2$).

Also, although comparisons of variances are not commonly performed in aggression research, SEM makes the decision to evaluate these differences explicit. Such comparisons are an important step in aggression research because they have the potential to reveal the degree of individual differences in aggressive behavior within a population. This consideration becomes especially important when comparing across different types of aggression, comparing different groups, and in longitudinal studies of aggression.

Finally, SEM represents a powerful approach to examining associations, whether directional (i.e., regression paths) or nondirectional (i.e., correlations), between variables. Because associations between latent variables are generally computed as covariances, they are dependent on both the degree of association between variables and the variability of the two variables. To
model associations in a common metric, however, we suggest using phantom variables. Even though SEM programs can output standardized estimates (i.e., correlations), such estimates cannot be directly tested for differences. The method of using phantom variables is valuable because it allows comparison of latent associations between different variables, across groups, or across time that are estimated in a common standardized metric.

Phantom variables are a second set of latent variables paralleling those already in the model; for example, Figure 1 displays a set of phantom variables that are linked to their respective latent variables. To achieve the standardization process, the variances of these phantom variables are fixed at 1.0, and the variances of the latent variables to which they are linked are fixed at 0. Information regarding latent variance is not lost, however, because this information is now represented as the regression coefficient ($\beta$) of the path between the phantom and original latent variables (with the latent variance equal to the square of this coefficient, $\beta^2$). The estimated covariance between the phantom variables of the constructs is now interpreted as a latent correlation (similar interpretations can be made of directional paths), and meaningful comparisons between different correlations in a model (e.g., comparing correlations between overt and social aggression assessed via self versus peer reports) can now be made using nested-model comparisons.

The latent correlations obtained in SEM are larger in magnitude than those obtained through correlating manifest variables because latent correlations are disattenuated (i.e., correlations between manifest variables underestimate true associations because each measure contains random measurement error). Latent correlations, however, represent the most accurate estimate of the true relation between two constructs. Moreover, significance testing of whether these correlations differ from some value (e.g., 0) will typically be more powerful when performed with latent rather than manifest variables.

In this section, we have highlighted the advantages of using latent variable SEM over traditional approaches to analyzing manifest variables when studying aggression, and hopefully have demonstrated the flexibility of SEM in estimating and comparing means, variances, and correlations among latent variables. In the next section, we will build upon these ideas in discussing the ability of SEM to compare these parameter estimates across different groups of individuals.

**Group differences in aggression**

Differences between males and females, across age groups, and across cultural settings in the mean levels, variances, and intercorrelations of aggressive behavior represent important foci of study. Most SEM packages have multiple-group options that allow these parameters to be compared across two or more groups. In addition to correcting all latent estimates across all groups for any degree of unreliability, SEM methods can be used to ensure comparability in the measurement of constructs across groups. This comparability is referred to as measurement invariance (for an excellent example of establishing measurement invariance of aggression constructs across gender, age, and cohorts, see Vaillancourt, Brendgen, Boivin, & Tremblay, 2003).

Three conditions are necessary to establish measurement invariance of constructs across groups (see Card & Little, in press; Little & Slegers, in press; Meredith, 1993). First, one must ensure that the basic structure of the model is equivalent across groups (known as configural invariance). Here, one simply ensures that the measurement structure is equivalent across groups by fitting a model within each group in which the indicators are specified to load on the same constructs across groups. Consider a situation in which a researcher wishes to fit the model depicted in Figure 1 to a sample of boys and a sample of girls. Configural invariance would be established if the same indicators load on overt aggression, but not on social aggression, among
both boys and girls. When establishing this and other levels of measurement invariance across
groups, one generally does not place any constraints on the latent parameters in the model (i.e.,
the latent means, variances, and covariances are freely estimated) -- these parameter estimates
can be meaningfully compared across groups only after measurement invariance is established.

The second step in establishing measurement invariance is to equate the magnitudes of the
indicator loadings across groups, a condition known as weak factorial invariance. Here, the
loading of each indicator on its respective latent construct (e.g., the loading of ‘hits others’ on
overt aggression) is constrained to be proportionally equal in magnitude across groups (i.e., the
loadings are weighted by the common factor variance which is allowed to vary across groups).
This constraint ensures that variances in the indicators translate into variance in the latent
constructs in a proportionally equivalent manner across groups. Weak invariance would be
established in our hypothetical model of Figure 1 if all six loadings ($\lambda$) could be reasonably
equated across boys and girls.

The third and final step in establishing measurement invariance across groups is to equate
the means of the manifest indicators ($\tau$), a condition known as strong invariance (see Little,
1997; Meredith, 1993). Considering again our hypothetical example, this step involves equating
the mean of each corresponding indicator (i.e., the paths from the constant to the manifest
indicators) across groups. This constraint does not imply that the mean levels of the construct are
constrained to be equal across groups; instead, any group differences in aggression are examined
as differences in latent means ($\alpha$). Equating the indicator means ensures that those aspects of a
construct that are relatively common in one group are also relatively common in other groups.
For example, if ‘calling others names’ was more common than ‘hitting others’ among boys, it is
necessary that ‘calling others names’ is also more common than ‘hitting others’ among girls in
order to ensure the equivalent measurement of overt aggression across gender.

Before concluding our discussion of establishing measurement invariance across groups, two
issues merit mention. First, establishing measurement equivalence is an issue of plausibility
rather than one of formal significance testing. Given that SEM is a statistically powerful
technique often used with large samples, even substantively trivial differences in measurement
across groups will often emerge as statistically significant. Therefore, although we recommend
progressing through the three steps outlined above primarily in order to detect if substantial
differences in measurement are evident between groups; for most applications in the social and
behavioral sciences, the final evaluation of whether measurement invariance is tenable should be
made based on the fit of the model after implementing the three sets of equalities describe above.
If the model with strong metric invariance across groups shows adequate model fit (e.g., RMSEA
< .08, CFI and similar indices > .90; see Hu & Bentler, 1995) then measurement invariance can
be concluded. Second, there exist several strategies for proceeding if strong metric invariance is
not plausible (see Card & Little, in press; Little & Slegers, in press; Millsap & Kwok, 2004).
These include removing constructs from the model for which measurement invariance is not
tenable, relaxing the offending cross-group constraints and analyzing models under partial
invariance, or choosing not to make cross-group comparisons. If measurement equivalence can
be established across groups, however, one can compare latent means, variances, and
correlations across groups using nested-model comparisons (described above).

Thus far, we have described SEM methods of modeling means, variances, and correlations
among aggression constructs that are commonly used in the study of one or more groups of
individuals, albeit with attention to some recent innovations in these techniques. In the next two
sections, we will describe more advanced applications of SEM in the study of aggression. First,
we will describe an approach similar to multi-trait multi-method decompositions that can be used
to disentangle the multi-dimensionality of aggression. Then we will provide recommendations
for studying the interdependent nature of aggression.

**The multidimensional nature of aggression**

Aggression is a multidimensional phenomenon, with distinctions commonly made in terms of the forms and the functions of aggressive behavior. The forms of aggression refer to the specific behavior enacted, and are often distinguished into those that are overt in nature (e.g., hitting, pushing, teasing, direct name calling) versus those that are more covert or indirect (e.g., excluding one from the group, spreading rumors, manipulating interpersonal relationships; e.g., Lagerspetz, Björkqvist, & Peltonen, 1988; Crick, 1996). Another distinction that has often been made refers to the function the aggression serves, and is commonly separated into that which is driven by instrumental motives (e.g., aggression to obtain social status or to receive tangible rewards) versus that which is reactive in nature (e.g., an angry aggressive response to a perceived threat or mistreatment; e.g., Dodge & Coie, 1987). In this section, we will briefly review problems in distinguishing these forms and functions using traditional analytic techniques, and present results of a study showing how they can be better disentangled through modified measures and SEM.

Traditional measures of aggression often yield extremely high interrelations between the different forms (typically ranging from \( r = .50 \) to .80; Card, Sawalani, Stucky, & Little, 2005) and functions (e.g., average \( r = .65 \); see Card & Little, 2005) of aggression. Although exploratory factor analyses have provided support for these distinctions based on form (e.g., Crick, 1996; Vaillancourt et al., 2003) and function (e.g., Day, Bream, & Pal, 1992; Poulin & Boivin, 2000), these high interrelations leave unanswered questions regarding the extent to which distinct correlates of different forms and functions of aggression can be detected.

Part of the reason for these high correlations may be due to the fact that traditional measurement procedures have confounded the discrete forms and functions of aggression. For example, typical items assessing different functions of aggression often share a form component (e.g., “I hit others to get what I want”, “I hit others if they make my made or upset”), which artificially inflates observed correlations. To remedy this problem, Little, Jones, Henrich, and Hawley (2003) developed a measurement strategy to disentangle the forms and functions of aggression. As shown in Figure 2, one can measure overt and relational forms of aggression by using items that are descriptive only of the behavior without reference to the function that the aggression may serve (e.g., “I’m the kind of person who hits, kicks, or punches others”, “I’m the kind of person who says mean things about others”). Then, one can use items that deliberately combine forms and functions of aggression to assess overt-instrumental (e.g., “I often threaten others to get what I want”), overt-reactive (e.g., “If others have angered me, I often hit, kick, or punch them”), relational-instrument (e.g., “To get what I want, I often gossip or spread rumors about others”), and relational-reactive aggression (e.g., “If others upset or hurt me, I often tell my friends to stop liking them”). Finally, as shown in Figure 2, SEM can be used to extract the latent form variance from these four latent form-function combinations, and the remaining functional information can be used to create latent variables representing the pure assessment of the instrumental and reactive functions of aggression.

Using this approach with a large sample of German adolescents, Little et al. (2003) found that overt and relational forms of aggression remained highly intercorrelated (disattenuated \( r = .83 \)), but the instrumental and reactive functions of aggression were essentially orthogonal (disattenuated \( r = -.10 \)). Further analyses of these pure forms and functions of aggression demonstrated important validity relationships that would not have been possible to detect with traditional approaches to measurement and analysis. For example, they showed that when the form of aggression is removed the pure information about reactive aggression is very highly related to both hostility and ease of frustration but that instrumental aggression is not. They also
showed that instrumental aggression is significantly more highly related with deliberate coercive strategies of influence than is reactive aggression (see Little et al., 2003, for details). These correlations with the mixed form-function measures of instrumental and reactive would have been contaminated and confounded by the form information (i.e., the overt vs. relational form of aggression) had SEM not been used to separate the sources of variability in the measures. Moreover, follow-up work showed that youth who are primarily instrumental in their aggressive behavior do not suffer the typical ill consequences of being aggressive relative to youth who are primarily reactively aggressive (see Little, Brauner, Noch, Henrich, & Hawley, 2003). The primary point here is that SEM procedures, in combination with carefully crafted measures, can be used to disentangle the many sources of variability that are common to most measures of aggressive and violent behavior and provide a critical analytic tool to test complex hypotheses about the nature of aggressive and violent behavior.

**Modeling the interdependency of aggression**

An emerging body of research suggests that aggression can be better understood by looking not only at the aggressors or the victims in isolation, but by considering the interpersonal relations between aggressors and victims (e.g., Pierce & Cohen, 1995). Adapting such a perspective has much to offer in understanding aggression, but is complicated by violations of assumptions of independence found in traditional analytic approaches (including traditional approaches in SEM). Fortunately, several approaches to managing the non-independence in interdependent data exist (for further discussion of modeling interdependent data using SEM, see Little & Card, 2005).

Before describing these approaches, two distinctions need to be made before deciding on an approach. First, one must determine whether the level of analysis is on dyads or dependencies within groups. Dyadic analysis is more appropriate when one wishes to focus on pairs of individuals (e.g., aggressor-victim dyads; Card & Hodges, 2005), whereas group-based methods are more appropriate when one wishes to model groups of three or more interacting individuals (e.g., play groups in which observations of interpersonal aggression are conducted; Coie et al., 1999). Second, one must determine whether it is more appropriate to consider individuals as exchangeable or distinguishable cases. Distinguishable cases are those in which each individual can be considered to have a distinct role, such as the aggressor in a unidirectional aggressor-victim relationship, whereas exchangeable cases are those in which there is no meaningful basis to assign individuals to certain roles (e.g., a child in a mutually aggressive dyad).

Dyads that consist of distinguishable members include non-twin siblings (in which siblings are distinguished by age), cross-sex friendships or romantic relationships (in which individuals are distinguished by sex), and aggressor-victim relationships (in which individuals are distinguished by their role as aggressor or victim). These situations can be analyzed using the Actor-Partner Interdependence Model (APIM; see Cook & Kenny, 2005), in which each dyad is considered a case, and the characteristics of the aggressors and their victims are represented as separate variables. In the APIM, relations among variables of one individual are considered actor effects, whereas relations among variables across individuals are partner effects.

Figure 3a shows a hypothetical example of relations among aggressors’ and their victims’ popularity at two time points. The relations of each individual’s popularity across time are considered actor effects, hence the stability of aggressors’ popularity and of victims’ popularity are considered actor effects. In contrast, the relation between aggressors’ popularity with the later popularity of their victims is considered a partner effect (e.g., a negative relation might be expected, such that being victimized by popular aggressors predicts decreases in victims’ popularity), as would the relation between victims’ popularity with the later popularity of those aggressing against them (e.g., this relation might also be expected to be negative, because
aggressing against unpopular targets might be reinforced whereas aggressing against popular targets might bring negative social ramifications). The most accurate estimates of these paths are obtained when SEM is applied so that these relations are not attenuated by measurement error. To our knowledge, no published studies have applied the APIM to aggressor-victim dyads, but we believe that this approach has considerable potential.

Examples in which dyads should be considered exchangeable include same-sex friendships, identical or same-sex fraternal twins, and mutually aggressive dyads in which there is no meaningful way to consistently distinguish dyad members. Here, the APIM is not appropriate because there is no non-arbitrary means to place one member of the dyad in one position versus the other. For these exchangeable case dyads, an alternative approach is the double-entry (intra-class) correlational approach of Griffin and Gonzalez (1995). This approach requires that each dyad be entered as two cases, alternating the order in which individuals in the dyad are entered.

Figure 3b depicts a hypothetical example of same-sex (exchangeable) friends’ levels of overt and social aggression, in which each child’s and his/her friend’s overt and social aggression are measured with three indicators (not portrayed for simplicity). In this model, $r_{\text{ind}}$ represents the disattenuated correlation between individuals’ overt and social aggression (corrected for dyadic dependency) and $r_{\text{dyad}}$ represents the association between pairs of friends’ overt and social aggression. In this setup, similarity between friends’ levels of overt aggression are represented as the square of the equated paths $\beta_{\text{overt}}$, and similarity in friends’ social aggression as the square of $\beta_{\text{social}}$. Standard errors (and resulting significance tests or confidence intervals) are based on a modified $N$ depending on the degrees of dependencies among dyads (see Griffin & Gonzalez, 1995).

These two approaches to analyzing dyadic data can be adapted to handle either type of situation. In the distinguishable case, one can double-enter the data but include a dummy-coded covariate that distinguishes the meaningful ordering of the dyad members (e.g., a dummy code of 0 when aggressors are entered before their victims and 1 when victims are entered before their aggressors; Gonzalez & Griffin, 1999). Similarly, the APIM can be adapted for the exchangeable case through a method of analyzing means and difference scores of the dyads (see Kenny, 1996).

Interdependencies occurring in small groups are commonly analyzed using the Social Relations Model (SRM; see Kenny, 1994). Although variations in group designs that can be analyzed exist, the most common is the round robin design depicted in Figure 3c. For example, Cillessen (see Coie et al., 1999; Lashley & Bond, 1997) observed interpersonal aggression in artificial play groups consisting of 6 boys each. Over the course of several play groups, observations were made of the number of aggressive acts each child made toward each peer. These values would be represented as x’s in Figure 3c. Note that the number of times Child 1 was aggressive against Child 2 is not necessarily identical to the number of times Child 2 was aggressive against Child 1, hence this matrix is nonsymmetric. The values on the major diagonal are missing because it is not expected that a child is aggressive against her/himself (and if s/he was, it would likely represent a qualitatively different phenomenon).

When considering interdependent group data, it is also necessary to decide whether individuals are distinguishable or exchangeable. For example, if observations of aggression are made in children’s play groups, there is no readily apparent distinguishing factor among the individuals, and would generally be considered exchangeable. The SRM is an effective method of analyzing these data, and programs to perform such analyses are readily available from Kenny (http://davidakenny.net/kenny.htm). A current limitation of the SRM with exchangeable case data is the inability to model parameters in latent space, so we will not discuss it further.

Groups can also be considered in terms of distinguishable roles. For example, Cook and Kenny (2004) examined patterns of perceived negativity within four person families. Because
each family member can be identified as having a distinct role (father, mother, older adolescent, and younger adolescent), these data are considered distinguishable cases. This type of SRM can be modeled as a latent variable SEM, as shown in Figure 3d. In this setup, it is possible to estimate means and variances at the level of the family (the degree of negativity across families), actor effects for each family member (e.g., older adolescents seeing others as negative), and partner effects for each family member (e.g., fathers being seen as negative), as well as generalized reciprocities for each family member (e.g., are mothers who perceive others as negative also perceived as negative?) and dyadic reciprocities for each dyad (are older adolescents who perceive their younger siblings as negative also perceived this way by their siblings?).

Conclusions

We have described basic techniques of analyzing means, variances, and correlations in one or more groups of individuals using SEM, then described more advanced applications of decomposing the multidimensional nature of aggression and modeling interdependencies inherent in the study of aggression. In doing so, we have offered some future directions for improving analytic techniques in the study of aggression. The topics we have discussed are only a small portion of those that could be considered when using SEM in research on aggression and violence (see chapters by Muthén, Nagin, this volume). Nevertheless, we hope that the brief introduction provided in this chapter illustrates to aggression researchers the power and flexibility of SEM in addressing a wide range of research questions.

Endnotes

1 A fourth step is possible but is not necessary for measurement invariance to hold. Namely, the residual variances of the indicators can also be tested for equality across groups. This condition is called strict invariance (see Meredith, 1993). This condition, however, is overly restrictive for comparing latent construct information and should not be enforced because it forces all potential sources of measurement bias into the latent parameter space (see Little, 1997).

2 Other within-individual effects would be considered actor effects, for example, if we looked at the concurrent or longitudinal relation of aggressors’ prosocial behavior on their popularity.
References


Figure 1. Hypothetical example of modeling overt and social aggression in SEM.

Note: In SEM manifest (i.e., measured) variables are represented as rectangles and latent variables are represented as ovals. Nondirectional paths (i.e., correlations, often indicated as $\theta$, when between manifest variables and as $\varphi$, when between latent variables) are represented as curved double-headed arrows between two variables. Double-headed arrows starting and ending at the same indicator variable, $\theta_{xx}$, represent the residual variance of the indicator, and those starting and ending at the same latent variable, $\varphi_{xx}$, represent the variance of the latent variable. Directional paths (i.e., directional regression paths), either from latent variables to manifest indicators of that variable (factor loadings, often indicated as $\lambda_{xy}$) or between latent variables (structural paths, often indicated as $\beta_{xy}$), are represented as single-headed arrows (with the arrow on the presumed dependent variable). Mean levels are indicated by the paths from the constant 1 (represented as $\tau$) to the indicators (these paths are often referenced as $\tau$) and latent variables (often referenced as $\alpha$).

Figure 2. Disentangling the forms and functions of aggression using SEM (from Little et al., 2003).
Figure 3. Modeling interdependency in studying aggression.