Analytic Considerations in Cross-Cultural Research on Peer Relations

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Analytic Considerations in Cross-Cultural Research on Peer Relations

In this chapter, we will review analytic strategies for examining various aspects of peer relations across cultures. Specifically, we will review techniques of comparing measures across cultural contexts, with an emphasis on Means and Covariance Structures (MACS) analysis. We will then describe the comparisons of mean levels, variances, and covariances across cultures using this approach. Next, we will describe techniques of examining intercultural perception and interaction using the social relations model, an underutilized approach in studying youths’ peer relations. Finally, we will briefly discuss some other analytic approaches, and offer our view of the state of the art and future directions for analyzing cross-cultural peer relations data.

Comparing cultures – measurement

Given that there is little consensus regarding the measurement of group-level status (e.g., peer acceptance and rejection, perceived popularity and rejection, victimization), dyadic relationships of liking (e.g., friendships, romantic relationships) and disliking (e.g., enemies, mutual antipathies), and interpersonal behaviors (e.g., aggression, prosocial behaviors, interpersonal withdrawal) even within cultures predominantly studied by peer relations researchers (i.e., primarily White, English-speaking youths), it is little wonder that measuring these constructs across cultures poses significant challenges. Although it is beyond the scope of this chapter to attempt to define these constructs or to offer specific suggestions of how these may be assessed in specific cultures, we wish to remind readers of the importance of this process. No amount of analytic sophistication can remedy problematic operationalization of a construct (though the methods we describe next can evaluate the success of cross-cultural measurement of a construct). Therefore, it is of critical importance that the researcher is familiar with both the constructs and the cultures being investigated. Moreover, although procedures for translating instruments across languages are well known, we also recommend that the translators are
familiar with the underlying constructs that are being assessed by individual items. This familiarity will avoid many of the ambiguities of items that may arise if they are translated across languages without a clear understanding of the construct that the items are meant to capture. Although good examples of this process are presented in the other chapters of this book, we emphasize that the expression “garbage in, garbage out” is especially relevant in poorly conceived cross-cultural research. After careful attention to these issues, the researcher can evaluate the success of the operationalizations and, if successful, begin to compare cultures in terms of the underlying constructs of interest. We present in this section an analytic approach to evaluating the comparability of assessment of constructs across cultures.

Mean and Covariance Structures (MACS) analysis represents a useful analytic tool for assessing construct comparability across cultures (see Little, 1997). Like confirmatory factor analysis, a MACS analysis models the latent commonalities among a series of indicators (items or parcels of a scale, different scales assessing the same construct) designed to assess the same construct. In addition to providing estimates of the loadings of each indicator onto the construct, overall fit of the modeled relations among indicators and constructs are provided (i.e., fit indices). MACS analysis differs, however, from traditional confirmatory factor analysis in that it also analyzes the intercepts of the indicators (and, with multiple groups, allows for comparison of latent variable means across groups, a topic described in the next section; see Little, 1997; Little & Slegers, in press).

As an example, imagine that a researcher is interested in studying peer victimization in two cultures (more than two could be examined), perhaps among children in the United States and China (for an example of assessing victimization among Chinese children see Schwartz, Chang, & Farver, 2001). After taking appropriate efforts to identify indicators adequately assessing different aspects of victimization (e.g., physical, verbal, and social) in both cultures, and following recommended procedures regarding translation of items (see e.g., Novy, Stanley, Averill, & Daza, 2001), these scales are administered to samples of children in each country. The researcher might then model the hypothesized measurement structure of these scales within the two cultures as depicted in Figure 1.

Measurement equivalence across cultures can be defined as equivalence in both loadings and intercepts of indicators (known as strong factorial invariance; see Meredith, 1993). In the victimization example displayed in Figure 1, this would mean that the loadings of each indicator onto the victimization construct ($\lambda_1, \lambda_2,$ and $\lambda_3$) would be equal in the United States and Chinese populations represented by the samples, as would the intercepts of each indicator ($\tau_1, \tau_2,$ and $\tau_3$). Although some might argue that the residual variance terms of the indicators ($\theta_1, \theta_2,$ and $\theta_3$) should also be equated across cultures (known as strict factorial invariance), we do not recommend this approach, as it could bias other parameters in the model by forcing culturally unique aspects of the indicators and random error into the structural portion of the model (see Little, 1997; Little & Slegers, in press; Meredith, 1993).

To assess (strong) measurement invariance across cultures one first fits an unrestricted model in which the indicator loadings ($\lambda_1, \lambda_2,$ and $\lambda_3$) and intercepts ($\tau_1, \tau_2,$ and $\tau_3$) are separately estimated within each culture (note that in order to identify the parameters and set the scale for the latent victimization constructs, the variances, $\psi_{11}$ in each culture are initially set to 1, and in order to identify the mean structure, the latent intercepts, $\alpha$s, are initially set to 0; see Little, Slegers, & Ledford, 2004, for details on alternative methods of identification that can also be used in these kinds of comparisons). In a second model, one restricts the indicator loadings ($\lambda_1, \lambda_2,$ and $\lambda_3$) and intercepts ($\tau_1, \tau_2,$ and $\tau_3$) to be equal across the (two or more) cultural contexts (and frees the construct variance, $\psi_{11}$, in the other cultures in order to avoid introducing unnecessary restrictions in the model). The unrestricted and restricted models are then compared in one of two ways. From a statistical rationale, one could perform nested-model comparisons between the unrestricted and restricted models, $\Delta \chi^2 = \chi^2_{\text{restricted}} - \chi^2_{\text{unrestricted}}$ with $\Delta df = df_{\text{restricted}} - df_{\text{unrestricted}}$.
However, especially with large sample sizes or when numerous restrictions are imposed, this approach is likely to indicate measurement inequalities across cultures even in the presence of substantively trivial differences. Alternatively, and as the approach we recommend, a modeling rationale would suggest that if the restricted model exhibits adequate fit as indexed by common fit indexes, than equality of measurement (i.e., measurement invariance) across the cultures can be concluded to reasonably approximate the data. Such fit indices include the Non-Normed Fit Index (NNFI), which is considered acceptable if greater than 0.90 (Bentler & Bonett, 1980) and the Root Mean Square Error of Approximation (RMSEA) which is considered adequate if below 0.08 (Steiger, 1990; see Brown & Cudek, 1993; Cheung & Rensvold, 2002; Hu & Bentler, 1995).

If measurement invariance across cultures can reasonably be concluded, then one can begin examining differences across cultures in the latent constructs, because constructs can be presumed to represent fundamentally similar phenomena in the cultures under investigation. If measurement invariance is not tenable, then several options must be considered (see Little & Slegers, in press). One must first determine which indicators most contribute to poor model fit and consider the size of this misfit (usually determined by examining modification indices and residuals of the restricted model described above). If it seems that the differences between the indicators are small enough that they are substantively equitable, one could argue that it is appropriate to proceed with cross-cultural equality constraints in place.

If there is a reasonable post-hoc explanation for why some indicators do not assess the underlying construct equally across cultures, then it is defensible to remove those specific indicators and model the latent construct only with those indicators that are invariant across cultures (if this is done, it should be fully reported in order to provide others with valuable information on assessing such constructs). Alternatively, one could relax the cross-cultural equality constraints on the offending indicators and proceed with latent variable analysis of this partially invariant model; the researcher then should cautiously interpret latent similarities and differences in this construct across cultures (see Millsap & Kwok, 2004). Finally, it might be necessary to conclude that measurement invariance can not be established using the indicators selected, and the researcher must reconsider how to better evaluate the constructs of interest across cultures in the next study (this, we hope, adds emphasis to our previous advice to place great attention to the initial operationalization across cultures).

Comparing cultures – differences in mean levels and variances

Once measurement invariance, or a reasonable approximation of it (e.g., partial invariance) is established, it is then possible to begin evaluating similarities and differences across cultures in the latent constructs. In this section, we describe techniques to compare cultures in terms of mean levels and variances of constructs.

In evaluating mean-level differences in the latent construct across cultures, one begins by freeing the implied restriction of 0 on the paths between the unit constant (i.e., the triangle in Figure 1) and the latent constructs of each culture; in other words, paths are added from the constant to the latent construct in each culture. Note that the mean structure of the model that includes estimated latent means ($\alpha$s) can now be identified because of the equating of the manifest intercepts ($\tau$s) across cultures, as this equating also gains back degrees of freedom.

In order to examine differences between means in the latent construct across cultures, one can simply compare nested models in which the less restricted model estimates construct means ($\alpha$s, the paths from the constant to the latent construct in Figure 1) in all cultures except the reference culture (which is set to 0 in order to provide a reference mean) versus a more restricted model in which the latent means ($\alpha$s) are set to be equal. The test of significance in the difference between the two models ($\Delta \chi^2 = \chi^2_{\text{restricted}} - \chi^2_{\text{unrestricted}}$ with $\Delta df = df_{\text{restricted}} - df_{\text{unrestricted}}$) indicates whether the means of the construct can be considered reliably different across cultures.
We would like to note that, in contrast to our view on using a modeling rationale for evaluating measurement invariance across cultures, we support the use of nested-model significance testing in evaluating cross-cultural differences in latent construct parameters (i.e., means, variances, and covariances). A modeling rationale is appropriate for cross-cultural comparison at the measurement level because we want to make conclusions regarding the reasonableness of the assumption of measurement equality across cultures. A statistical rationale is appropriate for comparisons at the latent level because we want to make probabilistic statements about differences between cultures (i.e., perform significance tests; see Little, 1997).

Of course, one should also evaluate the mean-level differences in terms of effect sizes in order to make conclusions regarding the importance of any statistically significant mean-level differences (e.g., Cohen’s $d$ for the difference between a culture’s and the reference group’s latent means, $d = \frac{\alpha_{Culture1}}{\sqrt{\frac{1}{2}(\psi_{11Culture1} + \psi_{11ReferenceCulture})}}$, could be computed as one effect size measure).

In comparing latent variances (i.e., $\psi_{11}$) across cultures, one adopts a similar approach to that of comparing latent means. Specifically, nested models are compared in which the less restricted model estimates the constructs’ variances in all cultures except the reference culture versus a more restricted model in which the latent variances are set to be equal. In both cases, the variance of the reference culture is set to 1 in order to identify the parameters and set the scale of the latent construct; note that this fixed parameter also identifies and sets the scale of the latent construct in other cultures because the factor loadings from the indicators are constrained to be equal across cultures (i.e, established by the measurement invariance constraints described above). The two nested models are compared using $\Delta \chi^2 = \chi^2_{\text{restricted}} - \chi^2_{\text{unrestricted}}$ with $\Delta df = df_{\text{restricted}} - df_{\text{unrestricted}}$ in order to evaluate differences in variances of the latent constructs across cultures. We note that comparisons of variances across cultures are uncommon in peer relations (and other) research, yet MACS analysis makes the decision to evaluate differences in latent variances explicit. Such comparisons, if more widely undertaken, have the potential to provide valuable information about the range of children’s peer experiences across cultures.

Considering again the victimization example shown in Figure 1, one begins by evaluating measurement invariance as described in the previous section. If substantive measurement invariance could reasonably be assumed (i.e., if the restricted model, with factor loadings $\lambda_1$, $\lambda_2$, and $\lambda_3$ and intercepts $\tau_1$, $\tau_2$, and $\tau_3$ equated across cultures, fits the data adequately), then one could evaluate differences in the latent means and variances across cultures (in this example, children in the United States and China). The unrestricted model would equate the factor loading and intercepts of the manifest indicators across cultures, and would set the latent variance in victimization to 1.0 and latent mean to 0 in the reference culture (in this example, the United States since the scales are more commonly used within this population), but would freely estimate the latent variances and means in the Chinese sample. The researcher then would fit two restricted models, one in which the latent victimization construct mean ($\alpha_1$) was restricted to be equal across the cultures, and one in which the latent victimization variance ($\psi_{11}$) was restricted to be equal. Comparison of each of these restricted models to the unrestricted model in terms of increase in $\Delta \chi^2$ (with $\Delta df = df_{\text{restricted}} - df_{\text{unrestricted}}$) would indicate differences in the latent victimization means and variances, respectively, between United States and Chinese children. Note that more than two cultures could be compared, and the tests described above would represent omnibus tests of differences across the cultures investigated, which could be followed up by a series of more specific comparisons.

Comparing cultures – differences in processes

In this section, we will describe a technique to compare cultures in terms of processes, or associations between constructs. Before beginning, however, we would like to emphasize the difference between comparing cultures in terms of mean levels (or variances) and comparing cultures in terms of processes. Comparison of mean levels, described in the previous section,
Analytic Consideration 9

Independent of the similarities or differences in mean levels between cultures are questions of differences in processes. Comparisons of processes answer questions of ‘Is X differentially related to Y in cultures A and B?’. Following the example of the previous section, one might evaluate whether rates of victimization among children differ between two cultures as a mean level comparison, but also consider whether victimization is more strongly related to social status in one culture relative to another as a process comparison. As mentioned, the answer to one question is completely independent to the answer of the other (the former can be considered a main effect and the latter an interaction, or moderated, effect).

MACS analyses can address differences in latent correlations across cultures simply by an elaboration of the approach described in the prior section. This approach, using associations between victimization and social status as an example, is depicted in Figure 2. Here, we have rearranged the locations of the different cultures (now on the top and bottom of the figure) only to simplify the figure. Notice that there are now two latent variables representing each construct in each culture. If we had represented the victimization and social status constructs with one latent variable each, the path connecting the two constructs would have been in covariance terms. This would be inadequate to test differences in association across cultures, as any differences in covariance would be the product of both differences in correlations and differences in variances across cultures.

To address this problem, we recommend an alternative approach (see Little, 1997) involving the creation of a second-order latent construct (e.g., $\eta_2$ in Figure 2) for each first-order construct (e.g., $\eta_1$). The variance of the first-order latent construct ($\eta_1$) is fixed at zero and the variance of the second-order latent construct ($\eta_2$) is fixed at 1.0 in both cultures. Information regarding variances is not lost, however, as this information is now contained in the regression coefficient between the two latent variables (e.g., $\beta_{12}$ in Figure 2). Note that the variance is still restricted in the reference cultural group, here at 1.0, but estimated in the other groups; thus the latent variance of this group is equal to the square of this coefficient ($\eta_2^2$). With this approach, however, we are now able to interpret the paths between the second-order latent variables of the two constructs ($\psi_{42}$ in Figure 2) as latent (i.e., disattenuated) correlation coefficients (an identical approach could be applied to directional effects between $\eta_1$ and $\eta_4$).

From here, comparison of latent associations (i.e., correlations) proceeds as described for latent means and variances. Specifically, nested model comparison between an unrestricted model in which the latent correlations ($\psi_{42}$) are separately estimated in each culture and a restricted model in which these latent correlations are constrained to be equal reveals differences in these associations across cultures. Using the example described, this test would examine whether the latent correlation between victimization and social status reliably differs between children in the United States and China (i.e., examine whether the latent correlation, $\psi_{42}$, is equal among children in the two cultures).

Analyzing inter-culture interaction – the social relations model

The reality of the modern world is that cultures do not exist in discrete, non-overlapping contexts; instead, youths of different cultures often interact. Modeling these interactions requires special techniques of analyzing data (i.e., dyadic, triadic, and other $n$-adic approaches). Here, we will describe the social relations model as a flexible tool for analyzing interpersonal perception, affect, and behavior, and suggest a method of using this approach for studying inter-cultural interaction.

Given that the social relations model has received little application in child and adolescent peer relations research (for exceptions see Coie et al., 1999; Hubbard, Dodge, Cillessen, Coie, & Schwartz, 2001; Malloy, Sugarman, Montvilo, & Ben-Zeev, 1995; Malloy, Yarlas, Montvilo, & Sugarman, 1996; Ross & Lollis, 1989; Scarpati, Malloy, & Fleming, 1996), we will first describe this model in brief detail. The social relations model is a conceptual,
methodological, and analytic approach that captures the interpersonal nature of perception, affect (i.e., liking and disliking), and behavior (see Kenny, 1994; Kenny & La Voie, 1984; Malloy & Kenny, 1986). Conceptually, it offers insight into the consideration of the dyadic nature of interpersonal interaction. Methodologically, it requires data to be collected so that dyadic measures (i.e., ratings, nominations, or behavioral observations of one individual toward another) from a set of youths are specifically directed toward another set of youths. Specific designs include half-block (one set of youths completes measures of a second, distinct set of youths), block (two sets of youths complete measures of youths in the other set, but not in their own set), round robin (youths complete measures of all peers), and block-round robin (youths in two sets complete measures of all peers, both those in their own set and those in the other set) designs (see Figure 3). Analytically, it provides a sophisticated method of managing the interdependency among these data (whereas traditional analytic approaches make assumptions regarding independence of observations that are clearly violated).

In its basic form, the social relations model provides information on three aspects of interpersonal perceptions, affect, or behavior: group means, variance partitioning, and reciprocity. First, it provides unbiased estimates of mean levels of variables within the entire groups. It also partitions the variance among these scores into that which is due to individual differences among those from whom the measure originates (i.e., perceivers, likers/dislikers, or those enacting the behavior), termed actor variance; that due to individual differences among those toward whom the measure originates (i.e., those perceived, liked/disliked, or receiving the behavior), termed partner variance; and, if the dyadic construct of interest is assessed using multiple items or at multiple time points, it is also possible to distinguish the uniqueness of scores (perception, affect, or behavior) between two individuals, after accounting for the actor’s tendency to have these scores toward others and the partner’s tendency to receive these scores from others, into that due to stable relationship effects and that due to random error. Finally, the social relations model allows the computation of two indexes of reciprocity. Generalized reciprocity refers to tendencies of individuals who perceive, like/dislike, or behave toward others in a certain way to also be perceived, liked/disliked, or behaved toward by others at a high or low rate. Dyadic reciprocity refers to the correlation between one individual’s perception, affect, or behavior toward a particular peer and that particular peer’s perception, affect, or behavior toward the individual.

To illustrate these concepts, consider a situation in which a researcher observes aggression within children’s artificial play groups (for an example of this type of study see Coie et al., 1999). The researcher might observe occurrences of aggression of all children with all possible peers (i.e., a round robin design). The overall frequency of aggression within that play group would be indexed by the group mean. It might be expected that some children, irrespective of the particular peer with whom they interact, would tend to more frequently behave aggressively (i.e., have a high actor effect), whereas other children would tend to rarely enact aggression (i.e., have a low actor effect). Individual differences in these tendencies to enact aggression toward peers would be indexed by the degree of actor variance. It is also likely that some youths would frequently be the targets of their peers’ aggression (i.e., have a high partner effect), whereas others would rarely be targeted (i.e., have a low partner effect); individual differences in these tendencies would be indexed by partner variance.

Now, imagine that the researcher observed that Adam very frequently hits Billy, even more than would be expected given Adam’s general tendency to hit others and Billy’s general tendency to be hit by others. If the researcher had other measures of aggression (e.g., how often Adam calls Billy names, how often Adam tries to exclude Billy from the group), or had observations at several time points (e.g., in playgroups on subsequent days), and Adam was found to be especially aggressive toward Billy on these other indicators as well, than it might be conclude that there is a relationship effect of high aggression from Adam to Billy (beyond
Adam’s general aggressiveness and Billy’s general victimization). The degree of differences among the dyads of this group, after controlling for the actor and partner effects of the individuals in the dyads, are indexed by the amount of relationship variance. The researcher might also examine whether children who are highly aggressive toward others are also frequently the targets of others’ aggression, which would be indicated by a positive generalized reciprocity correlation (alternatively, a researcher might find that children who are highly aggressive toward others are rarely the targets of others’ aggression, indicated by a negative generalized reciprocity correlation). Finally, the researcher might examine whether there is, across all dyads in the group, a positive or negative relation between a child’s aggression toward a particular peer (e.g., Adam’s aggression toward Billy) and that particular peer’s aggression toward the child (e.g., Billy’s aggression toward Adam); this is indexed by the dyadic reciprocity correlation.

Description of the computation of these parameters is beyond the scope of this chapter, but is described in detail in several other sources (e.g., Kenny, 1994; Lashley & Bond, 1997).

Although several methods of computing standard errors (for significance testing or computation of confidence intervals) of each estimate exist (see Lashley & Bond, 1997), we will briefly describe one of the more common approaches. If estimates of each of the above parameters (group means; actor, partner, and relationship variances; generalized and dyadic reciprocities) are obtained from several independent groups (e.g., separate playgroups or classrooms), standard errors of estimates of each parameter can be obtained by assessing the dispersion of these estimates among the groups (with estimates from each group weighted by number in group minus 1, if group sizes differ); specifically, the standard error equals the square root of the variance of parameter estimates across groups divided by the number of groups minus 1.

Although we have provided only brief description of the social relations model, we hope that this will serve as a foundation of basic understanding. More detailed overviews can be found in Kenny (1994), Kenny and La Voie (1984), and Malloy and Kenny (1986); and further information on the statistical details, including significance testing, can be found in Kenny (1994), Lashley and Bond (1997), and Lashley and Kenny (1998). We next describe an approach of decomposing social relations model designs in order to gain a better understanding of dyadic variables within and across cultures (for a similar approaches applied to adults’ cross-cultural perceptions, see Albright et al., 1997).

Consider another example in which interpersonal perceptions of a construct (e.g., perceived popularity) are obtained via peer reports within multi-ethnic classrooms. If all children are asked to report on all peers, than this could be represented as a round robin design. However, if we then decompose this round robin matrix according to the ethnicities of nominators and targets, than we can conceptualize these data as fitting a block-round robin design. For simplicity, we will imagine that our classrooms consist only of Caucasian and African American students (though multiple ethnicities could be considered), which would yield a 2 x 2 decomposition of the round robin matrix (see Figure 3; for a similar example considering children’s perceptions within and across sexes, see Card, Hodges, Little, & Hawley, in press).

The researcher can then analyze these submatrices as a series of round robin or half block designs. Returning to our example on perceived popularity, mean ratings of popularity (group means), individual differences in perceiving others as popular (actor variances), individual differences in being perceived as popular (partner variances), and differences among dyads in reliable unique perceptions of popularity (relationship variances) could be computed within each submatrix: African American students’ ratings of other African American students, African American students’ ratings of Caucasian students, Caucasian students’ ratings of African American students, and Caucasian students’ ratings of other Caucasian students. With estimates from multiple classrooms, ethnic differences in perceiving others, being perceived by others, and inter-/intra-perceptual difference would be indicated by the two main effects and the interaction
effect, respectively, of a 2 (perceiver ethnicity) X 2 (target ethnicity) repeated-measures ANOVA across classrooms. Generalized reciprocities could also be computed for the four ethnicity-rating groups, though the reciprocities of cross-ethnicity perceptions would consist of the correlations between the actor effects (i.e., row means) of one half block with the partner effects (i.e., column means) of the other half block (paralleling analysis of block designs); for example the correlation between African American students’ perceptions of Caucasian students (the row means of the upper right submatrix of Figure 3) with Caucasian students’ perceptions of the African American students (the column means of the lower left submatrix of Figure 3). Tests of ethnic differences by perceiver, target, and their interaction could then also be performed through a 2 X 2 ANOVA.

A special case is made for dyadic reciprocity; given that the correlation between African American students’ perceptions of particular Caucasian students and those particular Caucasian students’ perceptions of African American students represents all cross-ethnic perceptions, a one-way 3-level (African American, cross-ethnic, and Caucasian) repeated-measures ANOVA is used to assess ethnic differences.

Having discussed methods of computing group means, actor, partner, and relationship variances, and generalized and dyadic reciprocities in intra- and inter-ethnic perceptions (similar approaches could be used for measures of affect or dyadic behaviors), we will now discuss the interpretation of these effects.

Differences in group means indicate differences in mean levels of perceptions; nominator ethnic differences would indicate that one ethnic group perceives peers in general in a certain way more so than another ethnic group (e.g., African American or Caucasian students may differ in perceiving others as popular), target ethnic differences would indicate that one ethnic group is seen differently (e.g., as more popular) than another; and nominator X target interactions would indicate that there is an intra- or inter-ethnic bias (e.g., perceiving one’s own ethnicity as more popular), after controlling for the main effects of nominator and target ethnicity.

Differences in variance partitioning also offer interesting insight into interpersonal perception within and across groups. Ethnic differences in actor variances would indicate ethnic differences in the degree of individual differences in general perceptions of others. Nominator differences would indicate that there exists more variability within one group than another in generalized views of peers, whereas target differences would indicate that there exists greater variability of peers’ generalized perceptions of one group than another. Perhaps most interesting are nominator X target interactions, which can address questions regarding the degree of variability in same- and cross-ethnic perceptions. Differences in partner variances would indicate ethnic differences in consensus, or agreement among peers regarding who is high or low on a characteristic. Nominator differences would indicate that one group has greater consensus in their views of peers, whereas target differences would indicate that there is more consensus in the characteristics of one group relative to another. Nominator X target interactions would be indicative of greater within- or between-group consensus. Relationship variance indexes the uniqueness of interpersonal perception, and can be interpreted in a variety of ways, including unique behaviors enacted within the dyadic context (i.e., unique perceptions are due to witnessing different behaviors of the target than those observed by others) and differences in meaning systems assigned to similar behaviors (i.e., unique perceptions are due to viewing characteristics of the target differently than others). Either interpretation is substantively interesting in exploring the role of culture in peer relationships. Relationship variance is the variability in these unique effects, after removing measurement error, and can also be interpreted in terms of ethnic differences among nominators, targets, and nominator X target interactions.

Group differences in reciprocity also have promise in understanding the role of culture in peer relations. Generalized reciprocity can be interpreted as due to children’s self-perceptions influencing how they perceive peers (assuming that others’ perceptions correspond to self-perceptions), children’s perceptions of peers leading them to adopt behaviors that influence how
they are perceived by others, or children’s behaviors influencing both peers’ views of the child and the child’s perception of peers (possibly by eliciting certain behaviors from peers). Similar interpretations can be made for dyadic reciprocity, with the qualification that each of these processes are occurring within a dyadic (rather than group) context. Examination of group differences for generalized reciprocity (nominator, target, and nominator X target group differences) and dyadic reciprocity (differences among two intra-group reciprocity estimates and one intra-group reciprocity estimate) has the potential to reveal the extent to which these processes occur depending on the ethnicity (or other cultural factor) of the children or their peers.

We view potential group differences in (a) means, (b) variance partitioning among actor, partner, and relationship effects, and (c) generalized and dyadic reciprocities as potentially useful approaches to understand the role of culture in interpersonal perception, liking/disliking, and behaviors. However, the social relations model has not been widely utilized in peer relations research to date. One reason for this may be a lack of familiarity with the social relations model and the apparent complexity of the analyses. Furthermore, conceptualizing potential effects of culture is difficult if researchers are already unfamiliar with the social relations model. Despite these obstacles, we believe that the social relations model represents a valuable and highly flexible tool for studying processes within and across cultures in multicultural settings.

Fortunately, there exist several accessible introductions to the social relations model that can give researchers a useful start in using this approach (e.g., Kenny, 1994; Kenny & La Voie, 1984; Malloy & Kenny, 1986); moreover, Kenny (http://users.rcn.com/dakenny/kenny.htm) is developing user-friendly interfaces for the analysis programs (BLOCKO, SOREMO) commonly used.

Other advances include the translation of social relations model principles into more traditional approaches such as structural equation modeling. For example, one study (Branje, van Acken, & van Lieshout, 2002; see also Cook, 1994) examined the amount of support given among fathers, mothers, older children, and younger children using a round robin design within families. By modeling support between each combination of individuals (e.g., father to mother, father to older, father to younger, mother to father, mother to older, etc.), it was possible to model latent actor variances (e.g., the between-family differences in father’s support to other family members) and partner variances (e.g., the between-family differences in support received by younger children by other family members) for each role (i.e., father, mother, older, and younger). Relationship effects can also be modeled as the latent variance (i.e., that in common among multiple indicators) of each dyad after controlling for latent actor and partner variances. Furthermore, this structural equation modeling approach to roles also allows estimation of both covariances (i.e., generalized and dyadic). Thus, social-relations designs that include distinct roles for individuals have been accurately represented as structural equation models. Although we are not aware of prior research including mean values, it would also be possible to represent social relations models as MACS analyses; such an approach would provide all of the variance and covariance estimates of traditional social relations models plus allow mean level comparisons (e.g., do fathers or mothers provide more support within families). Although we have discussed a study involving family functioning, there is no reason that this approach could not be adapted to the study of peer relations.

Other analytic approaches

We have focused primarily on two general analytic approaches in this chapter, MACS analyses and the social relations model. Although this might seem quite limited, we would like to note that these are extraordinarily flexible approaches that can address a multitude of research questions besides those discussed in this chapter. Here, we will briefly mention some of these extensions, referring interested readers to more detailed descriptions.

Peer relations researchers, like most developmental scientists, often rely on longitudinal studies and analytic techniques (e.g., growth curve modeling). MACS analyses, like other
structural models, can be easily adapted to address questions regarding longitudinal growth trajectories (see e.g., McArdle & Epstein, 1987). Alternative person-centered approaches to studying trajectories of growth over time, such as Nagin’s group-based approach (1999; Nagin & Tremblay, 2001) and Muthén’s growth mixture modeling can also be modeled using MACS analyses (see Muthén, 2001). An advantage of representing growth-curve models (and other multi-level models) and person-centered trajectories as MACS analyses is that it allows one to evaluate cross-cultural equivalence of the measurement structures (advances in MACS analyses now allow for evaluation of cross-level interactions, so we view latent variable modeling as the generalized approach to these previously discrete techniques). We also note that in longitudinal research, it is important to assess measurement invariance across time as well as across cultures.

There also exist several variations of social relations modeling, such as the Weighted-Average Model of perception (WAM; see Kenny, 1991), extensions to examine similarity in perceptions among friends (e.g., Kenny & Kashy, 1994), and the Actor-Partner Interdependence Model (APIM; e.g., Kenny, 1996), that allow researchers to examine other dyadic phenomenon of cross-cultural interactions. Also, triadic (and higher order) extensions of the social relations model (Bond, Horn, & Kenny, 1997; Bond, Kenny, Broome, Stokes-Zoota, & Richard, 2000) allow for more analysis of more complex social interactions, which can also be recast to answer questions of cultural similarities and differences (e.g., do youths provide more protection against victimization toward their friends if the aggressor is of the same or different ethnicity?). Finally, the more general approach of social network analysis (see Knoke & Kuklinski, 1982; Wasserman & Faust, 1994) represents an extensive collection of strategies that can be utilized to answer many other questions involving peer relations of children of different cultures.

Conclusions and future directions

We believe that cross-cultural peer relations research is limited less by the availability of appropriate analytic techniques than by researchers’ efforts to study the wide range of unexplored issues (such as those described in other chapters of this volume)—this is not to say that sophisticated analysis is simple (as many readers of this chapter may agree), but we do believe that these techniques are accessible to those who wish to perform this research.

In this chapter, we have described two analytic approaches that can answer many of the questions posed by cross-cultural peer relations research. With MACS analyses, the evaluation of the cross-cultural measurement equivalence of constructs is made explicit. This measurement equivalence is important, because constructs such as aggression and victimization, group-level status such as popularity and social preference, and dyadic relationships such as friendships and mutual antipathies are likely to vary considerably in their manifestations across cultures (see e.g., Krappmann, 1996; Smith et al., 2002; and the chapters throughout this book). If it can be reasonably concluded that the constructs of interest are being similarly measured in different cultures (i.e., there is strong factorial invariance), then MACS analyses can examine all of the same aspects of more traditional analytic approaches—comparisons of means across groups (traditionally performed with analysis of variance), comparisons of correlations and directional paths among constructs (traditionally performed within a correlation or regression framework), growth curve analyses (traditionally performed as multi-level models), and person-centered approaches—all within a latent variable framework in which the constructs are equated across cultures. We therefore view MACS analysis as an extremely general approach that can be readily adapted to various research questions.

The other analytic strategy that we have presented, SRM, is a more specialized technique. We have chosen to highlight it based on our view that the interdependencies among children lie at the heart of peer relations research; they are not simply violations of traditional analytic assumptions to be avoided. Research has demonstrated the interdependent nature of aggressive behavior both in artificial play groups (Coie et al., 1999; Hubbard et al., 2001) and in school settings (Card, 2001; Card, Isaacs, & Hodges, 2000). Similarly, examination of friendships and
other dyadic relationships (e.g., mutual antipathies, parent-child relationships) necessarily involves consideration of interdependency, the degree of which is, again, of substantive interest rather than a nuisance to be overcome. We believe that SRM, and the related analytic approaches (e.g., APIM, WAM, triadic data analysis, social network analysis), represent an important set of analytic tools to help peer relations researchers conceptualize, study, and analyze the interdependencies that are inherent in this research. Consideration of the interdependencies within and between cultures, as we have demonstrated in our hypothetical example of perceptions of popularity among African American and Caucasian students, stands as an equally important future direction.

Although we have tried to be general with our presentation, we expect that as new research questions arise, it will be necessary to adapt these strategies to best answer these questions. Fortunately, the techniques we have described in this chapter are quite flexible, as we hopefully have demonstrated here. We believe that analytic techniques have evolved to the point that most questions of interest to peer relations researchers are answerable through available approaches. Thus, future research of cross cultural similarities and differences now lies with researchers’ creative asking of questions and their creative adaptation of analytic techniques.

References


Footnotes

1 An important additional aspect of actor variance is that there is within-person consistency. For example, if child A gives ratings high ratings of all peers and child B gives low ratings of all peers, actor variance is maximized to the extent that there is high between-actor variability but low within-actor variability. Similarly, partner variance is maximized when there is a high degree of individual differences but low within-person variability in ratings received.

2 To compute all components of the social relations model, the minimum number of individuals in any subgroup is four. If generalized reciprocities for the round robin of that subgroup are not estimated (i.e., they are fixed at zero), than the minimum number in a subgroup is three.

3 This method of evaluating ethnic differences in means is actually an unnecessarily low power test, as one could perform these analyses at the individual level using children’s estimated actor or partner effects (with identical results using either). We present this conservative method of computing group means at the subgroup level only because the researcher may wish to compare group means using this approach in order to parallel analyses on other social relations model parameters.

4 Currently, modeling social relations models as structural equation models (with or without means) requires that individuals within each group can be meaningfully assigned to specific roles. The reason for this is that dyadic measures (i.e., perceptions, liking / disliking, or behaviors) must be able to non-arbitrarily assigned to load on specific latent variables consistently across groups. Although we are not aware of current techniques that do not require specific roles, it seems possible that this limitation could be overcome with further development (e.g., through extension of current exchangeable case procedures for dyads; see Griffin & Gonzalez, 1995). Nevertheless, there exist numerous role classifications within the peer relations literature (e.g., sociometric classifications) that could meaningfully be used through existing approaches.
Figure 2. Comparing processes (latent correlations) across cultures.

Figure 3. Decomposition of round robin matrix to facilitate examination of intra- and inter-group perceptions.