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Improving the Measurement of Socially Unacceptable Attitudes and Behaviors With Item Response Theory

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Abstract

Assessment of socially unacceptable behaviors and attitudes via self-report is likely to yield skewed data that may be vulnerable to measurement non-invariance. Item response theory (IRT) can help address these measurement challenges. This paper illustrates application of IRT to data from a teen dating violence intervention study. Three factors reflecting teens' attitudes about dating violence were identified, and items from these 3 scales were subjected to IRT calibration and evaluated for differential item functioning (DIF) by gender. The IRT scores displayed superior measurement properties relative to the observed scale scores, and in 1 of the 3 factors, inferences about group mean differences were impacted by the presence of DIF. This application demonstrates how IRT analysis can improve measurement of socially unacceptable behaviors and attitudes.

Researchers have devoted considerable attention to the development of prevention and early intervention programs aimed at changing the manner in which youths think about and relate to themselves and others. Generally speaking, these programs strive to reduce the incidence of deviant behavior such as substance use, dating-related youth violence, and bullying. Although evidence suggests that some of these programs may be having the desired impact (e.g., Ellickson, McCaffrey, Ghosh-Dastidar & Longshore, 2003; Foshee et al., 2004; Frey et al., 2005; Wolfe et al., 2003), careful assessment of these interventions can be hampered by two measurement challenges that have not been fully recognized or addressed by the field. In our view, continued progression of knowledge in the adolescent prevention field can benefit from wider understanding and appreciation of the value of modern measurement theory and methods in addressing these challenges.

Accurate assessment of intervention effects that target socially unacceptable behaviors and attitudes is difficult primarily because respondents are unlikely to report engaging in socially unacceptable behaviors or to endorse attitudes that condone these behaviors. As a result, items and scales developed to measure these constructs typically yield highly skewed response distributions, especially in samples from the general population that are typical of prevention studies. The skew in these responses makes the assumption of continuity untenable, requiring that raw responses be collapsed to two or three response categories and modeled as binomial or multinomial outcomes. Not only does this practice obscure variability that may be of interest, it also limits the types of analyses that can be performed.

An additional challenge is that these measures may fail to display measurement invariance (Reise, Widaman, & Pugh, 1993) according to important demographic subgroups of interest. At the item level, non-invariance indicates non-equivalent measurement properties for individuals who have the same overall level of the measured construct, but are from different subgroups. For example, items assessing attitudes about dating violence may be particularly vulnerable to non-equivalence according to gender. Teens of both genders may have similar levels of acceptance of dating violence, but be differentially accepting of items that portray particular types of violence, or represent the male as victim rather than perpetrator. The potential non-equivalence across groups can confound interpretation of observed group differences. To avoid this possible confound, non-equivalence should be evaluated and taken into account in modeling.

Addressing skewed response distributions and potential measurement non-invariance is difficult with classical test theory approaches, but can be handled to some degree with item response theory (IRT; Hambleton & Swaminathan, 1985). No analytic technique can change a distribution that is mostly zeros into one that is normal, but IRT can help. First, IRT scoring converts categorical responses into an interval scale allowing for analysis of continuous outcomes. Second, this non-linear conversion helps alleviate the impact of highly skewed data by accentuating differences between 0 and 1 and attenuating differences between single intervals higher up on the scale. Thus, IRT allows one to assign different weight to responses depending on where they are on the scale. Furthermore, IRT is well-suited to evaluation of item and scale invariance through assessment of differential item functioning (DIF; Holland & Wainer, 1993), and provides a useful framework for modeling DIF to yield IRT scores that take the identified DIF into account.

This paper illustrates the application of IRT to data collected as part of an ongoing intervention study of dating violence among teens (Jaycox et al., under review). Youth dating violence is a problem of paramount importance. Various studies indicate that roughly 20% of all youths have been in abusive dating relationships (Aizenman & Kelley, 1988; Arias, Samios, & O'Leary, 1987; Bergman, 1992). Focusing solely on past year prevalence estimates in high school students, approximately 10% of girls and 9% of boys report exposure to dating violence (Grunbaum et al., 2002). An emerging body of evidence suggests that exposure to youth dating violence may have pernicious consequences, leading to increased substance abuse, unhealthy weight control, poorer health, sexual risk behavior, pregnancy and suicidality among victims (Silverman et al., 2001; Waigandt et al., 1990).

In the intervention study providing data for this application, scales reflecting attitudes about dating violence were planned as the main outcome measures. The scales consisted of multiple items with polytomous Likert-type response options, and the intention was to treat them as continuous measures for analytic purposes. However, routine treatment of these data proved unsatisfactory because of the two measurement challenges discussed above: the response distributions of these items were highly skewed, and the item content made measurement invariance across gender highly suspect (i.e., items addressed opposite-sex dating violence with each gender as perpetrator and victim). For example, the meaning of an item such as “It is okay for a girl to hit a boy if the he hit her first” may be somewhat different for a female versus a male respondent, since the respondent may identify more with the person of the same gender. Therefore, in an effort to optimize the precision of the outcome measures, after determining the factor structure of the item set, we used IRT to evaluate item and scale invariance with respect to gender. As part of this process, we also examined the properties of various scoring metrics (i.e., raw scores, IRT scores that ignore gender DIF, IRT scores that account for gender DIF) to identify the best metric for future analyses. Before describing this application, we first provide a brief overview of IRT and describe the characteristics of IRT that are particularly useful in this context.

Item response theory

IRT comprises a collection of modeling techniques that offer many advantages over classical test theory. By considering the correlations among the item responses, IRT extracts more information from the data than does classical test theory. Thus, more information can be gained about the relationship between the items on the test and the construct being measured (Embretson, 1996; Hambleton & Swaminathan, 1985;Lord, 1980). An IRT model specifies the relationship between an individual's observed responses to a set of items and the unobserved (or latent) trait that is being measured by the item set. One result of an IRT calibration is a set of continuous trace lines, most commonly defined as logistic functions, which describe the probability of endorsing each response category of an item given the scale value of the latent construct being measured.

For items with dichotomous responses, the two-parameter logistic (2PL) model is often applied. This model yields a trace line that is described by the location (*b*) and slope (*a*) parameters. The *b* parameter is the point along the trace line at which the probability of a positive response for a dichotomous item is 50%. The larger the location parameter, the more of the measured construct a respondent must have to endorse that item. The *a* parameter represents the slope of the trace line at the value of the location parameter and indicates the extent to which the item is related to the underlying construct. A steeper slope indicates a closer relationship to the construct.

A generalization of the 2PL model that permits estimation of multiple difficulty parameters associated with ordinal responses is Samejima's graded response model (Samejima, 1969, 1997). Let θ denote an individual's underlying value on the latent construct of interest. A general statement of Samejima's graded model, for ordered responses $x = k$, $k = 0, 1, 2, \ldots, m$, is:

$$T(x=k) = T^*(k) - T^*(k+1) = \frac{1}{1+\exp\left[-a_i\left(\theta - b_{ik}\right)\right]} - \frac{1}{1+\exp\left[-a_i\left(\theta - b_{ik+1}\right)\right]},$$

in which a_i is the slope parameter, b_{ik} is the item location parameter, and $T^*(k)$ is the trace line for the probability that a response is in category k or higher, for each value of θ.

IRT-Scores. In IRT, the relationship between the item responses and the latent trait (as represented by the item trace lines) is used to convert item responses into a scaled estimate of θ. The trait estimate is on an interval scale that is usually arbitrarily defined with a mean of 0 and a standard deviation of 1, resulting in a score distribution that is similar to the z-score distribution (Suen, 1990). Estimating a score using IRT methods involves the multiplication of all the trace lines corresponding to a person's responses to each question. For example, on a three-item test, a response of "no" to the first two items and "yes" to the third item would result in three trace lines. A posterior distribution is formed by multiplying the three trace lines together with a prior distribution (that is usually normal) for the unknown latent construct θ, and the IRT-score is calculated as the average of this posterior distribution (Thissen & Wainer, 2001). One of the unique features of IRT is that the reliability of the score estimate is variable, and depends on where the score lies along the underlying continuum (Hambleton & Swaminathan, 1985; Suen, 1990), thus IRT scores for individuals have associated standard errors of measurement that reflect the uncertainty of the estimated score.

IRT and Differential Item Functioning. An IRT model is ideally suited to defining differential item functioning (DIF), which can refer to situations in which items behave differently for various subgroups after controlling for the overall differences between subgroups on the construct being measured (Holland & Wainer, 1993; Thissen, Steinberg, & Wainer, 1988). For example, if the statement "It is okay for a girl to hit a boy if the he hit her first" contains gender DIF, the item trace lines will be different according to gender, either in the sense that the probabilities of endorsement are uniformly unequal for the two groups (the *b* parameters are different), or that the item is more discriminating for one group than the other (the *a* parameters are different). In either case, the presence of DIF implies the need for different item parameters according to group membership, and different item parameters yield different trace lines, resulting in different scores. Thus, a scale containing an item with DIF according to gender, for example, would yield non-identical IRT-scores for males and females whose response patterns were *exactly* the same, provided that the DIF was identified and accounted for in the scoring algorithm.

The fact that DIF is characterized by the need for unique item parameters according to group membership means that DIF can be specifically modeled, and can also be detected by testing the statistical significance of differences between item parameters for the two groups. There are a number of ways to construct such statistical tests. One approach that is applied in this paper uses model-based likelihood ratio comparison tests to evaluate the significance of observed differences in parameter estimates between groups (Thissen, Steinberg, & Wainer, 1993; Wainer, Sireci, & Thissen, 1991).

The model comparison approach has several advantages: it can be performed using available software (e.g., MULTILOG, Thissen, 1991; IRTLRDIF, Thissen, 2001), the definition of DIF is intuitive and clear (a statistically significant difference between item parameter estimates for the two groups), and the likelihood-based model comparison test is a common statistical test with known distributional properties. It also has been suggested that DIF analyses employing model-based likelihood ratio tests are more powerful than are other DIF detection approaches (Teresi, Kleinman, & Ocepek-Welikson, 2000; Thissen et al., 1993; Wainer, 1995).

To construct the nested model comparisons, the groups first must be linked so that the items for both groups can be calibrated simultaneously. The linking serves as a basis for which to estimate the group mean difference. The best way to link the groups is to identify a subset of items, referred to as "anchor items," that are judged *a priori* to be unbiased, and to use these as a basis with which to link the groups (Embretson, 1996). Recent research on the likelihood-based model comparison approach to DIF detection indicates that a single-item anchor is often sufficient to reliably estimate the group mean difference (i.e., link the two groups), although an anchor set of 3 or more items is preferable (Wang & Yeh, 2003). If there is no *a priori* set of anchor items, they can be identified in an iterative fashion. The iterations serve to "purify" the linkage, which is first accomplished based on all the items in the scale (except the item being tested), and finally based on only those items judged to be DIF-free. This purification process is common to many linking and equating procedures (e.g.Baker, Al-Karni, & Al-Dosary, 1991; Candell & Drasgow, 1988; Raju, van der Linden, & Fleer, 1995).

Once a set of anchor items has been established, each of the studied items can be tested for DIF relative to the now-specified anchor. For each studied item, all of the item's parameters can be first tested as a group by comparing the fit of a model that estimates separate item parameters for the two groups to the fit of a model that constrains these estimates to be equal for the two groups. If this model comparison test indicates that at least one of the study item's parameters might differ between groups (e.g., at a nominal $\alpha = .05$), parameter-specific model comparison tests can be constructed and evaluated in a similar fashion so that the source of the DIF can be identified.

In this study, we used modern measurement theory to first identify the factor structure of a group of items reflecting adolescents' acceptance of various forms of cross-gender aggression. Next, we refined our measurement of the identified factors using IRT, testing each of the items for DIF according to gender, and evaluating the impact of the identified DIF on inferences about group differences. The method and results are described below, and implications for measurement of this particular construct, as well as extreme attitudes in general are discussed.

Application

Data and Sample

Participants. Data are from a study evaluating a dating violence prevention curriculum. This evaluation employed an experimental design with random assignment by cluster of 9th grade Health classes in Los Angeles United School District (LAUSD). Eligible high schools were those serving majority Latino populations. Clusters were assigned to an immediate or delayed intervention (control group) and both groups were followed for 6-months. This study uses responses from the first survey administration, (i.e., the baseline survey prior to any student receiving the intervention), for a sample of N=2575.[1] The sample was nearly evenly split according to gender with 1263 males and 1312 females. The majority (91%) of the participants were Latino, with an average age of 14.5 years (SD= 1.04).

Measure. Analyses examine 14 items reflecting adolescents' attitudes about aggression in dating situations. Eight of the items were drawn from the Prescribed Norms scale (Foshee et al., 1996), and ask respondents to indicate on a 4-point scale (1=Strongly Agree to 4=Strongly Disagree) their extent of agreement with statements about dating violence (e.g., "Girls sometimes deserve to be hit by the boys they date", "It is ok for a girl to hit a boy if he hit her first"). These 8 items were reverse-scored for analyses so that for all items, a higher score indicated more acceptance of violence. Six additional items were between-gender items from an approval of retaliation scale (NOBAGS; Huesmann & Guerra, 1997). These items ask participants to indicate on a 4-point scale (1=Really Wrong to 4=Perfectly OK) the extent to which the response to the situation was acceptable (e.g., "Suppose a girl says something bad to a boy, do you think it's wrong for the boy to scream at her?"). Abbreviated content for all 14 items is listed in Table 1.

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[1] The analyses reported in Jaycox et al. (2005) use a sample of 2540 students because those analyses excludes blocks of schools (including both those randomized to intervention or control condition) where at least one school failed to provide data or complete the program as assigned. The responses from all students provide information on the measurement model and are included in the current application.

Analytic Approach

Assessing Dimensionality. After examining the descriptive statistics for all items, exploratory factor analyses (EFA) were conducted on the 14 items to determine their factor structure and create appropriate scales for further analysis. All items were assumed to be categorical for these analyses, which were conducted in Mplus (Muthen & Muthen, 1998-2004) using the unweighted least squares estimator. EFA solutions were examined for the entire sample as well as separately for boys and girls. Several criteria were used to determine the optimal number of factors, including the number of eigenvalues>1, the scree plot of the eigenvalues, the interpretability of candidate solutions, and the extent of correspondence across male and female respondents.

IRT DIF Evaluation and Scoring. Factors identified in the EFA were examined separately using Samejima's graded IRT model. First, the scales were evaluated for gender DIF using the likelihood ratio approach implemented with the freeware program IRTLRDIF (Thissen, 2001). The parameter-specific DIF significance evaluations were adjusted for multiple tests using the Benjamini-Hochberg adjustment (Benjamini & Hochberg, 1995) and an overall alpha level of .01. Although these criteria for significance are rather stringent, it is appropriate to control for multiple tests in the absence of any *a priori* hypotheses (i.e., when all items are being tested for DIF). Additionally, the model comparison approach to DIF detection is fairly powerful (Teresi et al., 2000; Wainer, 1995), and we were interested in accepting DIF only when there was strong evidence for its presence.

On the basis of the DIF analyses, we specified a version of Samejima's graded IRT model that allowed item parameters with DIF to vary by gender for each scale. The model parameters were estimated and IRT scale scores generated using MULTILOG (Thissen, 1991), which generates item parameter estimates and standard errors, together with other summary statistics, including item information, reliability estimates, and the focal group overall mean and standard deviation (relative to a $N(0,1)$ distribution for the reference group). In this application, the boys served as the reference group, and the girls comprised the focal group.

Model checking. Although there are currently no formal absolute tests for IRT model fit, there are some methods for examining the appropriateness of the model. We performed two distinct checks to determine whether the model was an adequate refection of the data. First, we visually examined the concordance between the observed and model predicted category responses for each item using bar charts. Strong concordance in these charts would imply that the model is able to re-create the data. Second, we examined non-parametric models of the item responses using TESTGRAPH (Ramsay, 1993) to evaluate whether the functional form imposed by the parametric IRT model was reasonable. In this examination, similarity between the shape of the category response functions from the parametric and non-parametric analyses would lend support for the IRT model.

Evaluating scores. The impact of allowing for DIF between genders on the models and scores was evaluated in several ways. First, plots of category, item, and scale response functions were generated to provide a visual representation of the effect size of the DIF. Next, to examine the impact of the DIF more closely at the factor-score level, IRT-scores were generated for each factor from models that specified the DIF and models that ignored the DIF. Correlations between the DIF-adjusted and non-DIF-adjusted IRT scores, as well as between each of these IRT scores and observed scale scores were calculated for each factor, and the corresponding scatterplots were examined to determine the impact of the IRT calibrations on the score distributions. In these plots, a lack of correspondence between the IRT scores and the scale scores would imply that the IRT scoring approach impacts the score distribution (presumably in an advantageous way), and a lack of correspondence between the IRT DIF-adjusted and IRT non-DIF-adjusted scores would indicate that the DIF "matters" and should be incorporated into the scoring model. Finally, t-tests comparing males and females on each of these three types of scores were generated for each of the factors to determine whether the scoring had an impact on the estimated group mean differences. Specifically, if the inferences about group differences varied according to the type of score used, the use of IRT-scores (either DIF-adjusted or non-DIF-adjusted) for modeling these factors as outcomes would be supported.

Results

Assessing Dimensionality. The exploratory factor analysis generated 4 eigenvalues>1. Solutions for up to 4 factors were examined, and the 3-factor solution was adopted for this set of items. The 3-factor solution yielded distinct item loadings, and provided a better fit to the data than the 2-factor solution. Additionally, all three factors were clearly interpretable, and the solution was similar across genders. In this solution, displayed for the full sample in Table 1, 5 of the 8 Prescribed Norms items (PN) loaded only on the first factor (PN1-PN4, PN6; Cronbach's alpha=.88). These items all involve boys hitting their girlfriends under minimal provocation. The distributions of responses to these items were highly skewed and they had very little variance – almost all respondents chose the "strongly disagree" or "somewhat disagree" options for these items. The second factor consists of 3 items from the NOBAGS scale (NB) and two from Prescribed Norms scale: NB3, NB4, NB5, PN5, and PN8 (Cronbach's alpha=.71). These are all items about girls' aggression on boys after some provocation. Item PN5 loaded significantly on both the first and second factors, but because of the content, it was included in the second factor. The third factor has 4 items: NB1, NB2, NB6, and PN7 (Cronbach's alpha=.55). These items are all about boys' aggression on girls after some provocation. Item PN7 loaded significantly on both the first and third factors, but because of the content, it was included in the third factor. Although the internal consistency for this factor was low, we felt that the factor analysis results and the commonality of the items' content strongly indicated that there was a distinct construct to be measured. In addition, even with low reliability the factor would be adequate for use as an outcome for purposes of evaluating an intervention, although the low reliability would limit the power for detecting program effects.

IRT DIF Evaluation and Scoring. We used IRT to calibrate the three derived scales from the 14 items, and evaluate the items within each scale for DIF according to gender. Table 2 shows the results of the DIF analyses for the three factors. For Factor 1, we identified 1 anchor item (item PN3), and 2 items, PN2 and PN6, displayed significant DIF. Item PN2 had DIF in both the *a* and *b* parameters, and item PN6 had only *b* DIF. For Factor 2, we identified 3 anchor items (items B3, B4, and PN5). Items NB5 and PN8 displayed significant *b* DIF. For Factor 3, we identified 2 anchor items (items NB2 and PN7), and item NB6 displayed significant *b* DIF. For all three factors the remaining items not explicitly mentioned here showed potential DIF in our initial screening and did not meet the criteria for being anchor items. However, in the final analyses with the chosen anchor items, these items did not have significant DIF according to the stringent criteria used in this application.

The next step was to estimate the parameters of the chosen model for each factor using MULTILOG. The item parameter estimates and their standard errors from these final calibrations are reported in Table 3. The items for all three factors tended to be fairly discriminating with all but one slope estimate exceeding 1.2. In this context, a slope of 1 corresponds to a factor loading of about .5, and a slope of 2 to a factor loading of about .76 (McLeod, Swygert, & Thissen, 2001; Takane & de Leeuw, 1987). The magnitude of the item slopes for Factor 1 are somewhat misleading, however, as they are most likely artificially inflated due to the high degree of covariance relative to variance in these items. The *b*-parameter values indicate that higher response categories corresponding to items in Factor 1 tend to be endorsed only at high levels of acceptance of violence (e.g., all b_3 values for Factor 1 are higher than 2), whereas items in the other two factors, particularly Factor 2, represent a broader segment of the underlying continuum they are measuring. The location parameters for each factor are all estimated relative to a mean of 0 for the boys. Overall, the girls had lower acceptance of violence than boys on all three factors with means of -.45, -.10, and -.20 for Factors 1-3 respectively.

Assessment of fit strongly supported the use of the IRT models for the items of Factors 2 and 3, whereas the strong inter-item correlation for Factor 1 might be inconsistent with the assumptions of the IRT model causing some lack of fit. For all three factors, the model-predicted category responses for each item corresponded very closely with the observed frequencies, lending support for the models. The non-parametric item response functions were also reasonably similar to their model based counterparts, with the exception of items in Factor 1; the category response functions for items in this factor were steeper and more distinct in the parametric models than in the non-parametric analysis. This is most likely due to the high degree of covariance among the item responses (65% of respondents answered 1 to every item on factor 1), which is utilized directly by the parametric model but not by the non-parametric model. In light of the lack of correspondence in item trace lines across the two analyses, the parametric IRT model and corresponding scores for Factor 1 should be interpreted cautiously.

Figure 1 shows the category (top panel) and item (bottom panel) response functions for girls and boys for item NB5 from Factor 2 ("Suppose a boy hit a girl, do you think its OK for the girl to hit him back?"). As shown in Table 3, the three location parameters for this item are all lower for boys than for girls. Thus, the DIF in this item indicates that controlling for the overall acceptance of girl-on-boy violence, boys are slightly more accepting than girls of this particular act, being less likely to say it is "really wrong" and more likely to say it is "perfectly OK." This results in boys having a higher expected score on this item than girls with the same level of overall acceptance of girl-on-boy violence.

Item PN6 from Factor 1 and item PN8 in Factor 2 also show this pattern of DIF (see parameter values in Table 3). The DIF in item PN2, Factor 1 is more difficult to interpret because of the difference in the slope parameters. Essentially, this item ("A girl who makes her boyfriend jealous on purpose deserves to be hit.") is more strongly related to the underlying construct of acceptance of violence for girls than for boys. Finally, the observed DIF in item NB6 from Factor 3 ("If a girls hits a boy, do you think its OK for the boy to hit her back?") indicates that controlling for the overall acceptance of violence, girls are slightly more accepting than boys of this particular act, being less likely to say it is "really wrong" and more likely to say it is "perfectly OK."

Figure 2 displays girls' and boys' expected total scores for each factor as a function of overall acceptance of violence. This relationship is generated based on the IRT model that specifies separate item parameters for the DIF items (i.e., the parameters in Table 3), so the expected total scores differ for boys and girls (if the model did not account for DIF, the two lines would be completely coincident). In general for Factor 1 (top panel), the DIF does not have a great deal of impact at the factor level (the expected total score lines for girls and boys are nearly coincident across the continuum), but boys do have slightly higher expected total scores for this factor than girls with the same overall level of acceptance of violence, especially at levels of acceptance of violence between 0 and 1. Modeling the DIF in Factor 2 also results in higher expected total scores for boys than girls. The effect is perhaps less pronounced than in Factor 1, but is more constant across the continuum of acceptance of violence. The effect of DIF on the expected total score for Factor 3 is in the opposite direction. For this factor, modeling the DIF results in higher expected total scores for girls than boys. The effect is slight, but discernable between acceptance of violence values of 0 and 2.

A final set of descriptive analyses was conducted to inform the decision regarding the most appropriate type of scores to use in future analyses, the observed scale scores, the DIF-adjusted IRT scores, or IRT scores that ignore the DIF. Scatterplots of the scale scores and DIF-adjusted IRT scores, such as that shown in Figure 3 (for Factor 3) provided a visual representation of how the IRT rescaling affects the score distribution. (The scale scores range from 5-20 for Factors 1 & 2, and 4-16 for Factor 3). In general, the IRT scores give more weight when moving up one scale score point at the very bottom of the scale than when moving up one point somewhere else on the scale, implying that according to the IRT model, endorsing violence to any extent is a bigger step than endorsing it a little more than others who have endorsed it. At the high end of the scale, the change in one scale score point is less important.

The shape of the scatterplots confirmed that the IRT scores would be useful, but did not clarify whether it was necessary to adjust for the small amount of observed DIF in the factors. To inform this decision, the estimated group mean differences between girls and boys were examined on each of the factors using the three different types of scores. This information, listed in Table 4, indicates that regardless of score type, boys have higher means than girls (more accepting of violence) for all 3 factors. For Factors 1 and 2, the results are the same regardless of type of score. However, the significance of the group differences varies for Factor 3 depending on which type of score is used. For Factor 3, the difference between girls and boys is *only* significant using the DIF-adjusted scores. Thus adjusting for the DIF has an impact on inferences about group means for 1 of the 3 factors. Based on this information, we made the decision to use DIF-adjusted scores in future analyses of these data so that observed gender differences could be confidently interpreted as true differences, not confounded by a lack of measurement invariance.

Discussion

Measurement of socially unacceptable behaviors and attitudes poses difficult challenges not easily met by classical test theory methods. Although many individuals do not endorse item responses reflecting agreement with extreme attitudes, real variability in attitudes about behaviors such as dating violence does exist. Accurate assessment of these constructs is essential to inform decisions of policymakers and prevention and intervention specialists on how best to influence change.

IRT methods offer some potential advantages over methods derived from classical test theory. IRT can convert categorical responses to an interval scale and can help alleviate the impact of skewed response distributions. In addition, IRT provides a useful framework for the evaluation of measurement invariance through DIF analyses. In the IRT framework, any significant lack of measurement invariance that is identified can easily be examined and accounted for in both the parameter estimates and resultant scores. The most obvious source of non-invariance in studies of cross-gender aggression would be according to gender.

In the application presented here, we found some items that were invariant and could act as anchor items, and other items that appear to be interpreted somewhat differently by boys and girls. Given the fact that societal norms are more lenient about female-on-male violence than male-on-female violence (e.g., Price & Byers, 1999), it is not surprising that boys and girls might respond to some items differently based on looking at the problem from differing perspectives. However, such differences can be very troublesome in studies that include both genders. Basic gender differences, differential program impact on boys and girls, and interactions with gender could be misleading if the items are behaving differently based on gender. Thus, IRT's capacity to account for DIF can increase precision in measurement, and lead to a greater ability to evaluate hypotheses.

As this application demonstrates, IRT analysis can help address the measurement challenges associated with assessment of socially unacceptable behaviors and attitudes. However, an important lesson learned is that the measures currently in existence to assess attitudes related to dating violence (and other related constructs) are not optimal. Further research to improve the assessment of socially unacceptable behaviors should consider non-standard approaches to item generation. For example, in order to understand the nuances in teen attitudes towards cross-gender aggression, our research team has begun work that allows teens to articulate their thoughts about dating violence scenarios as they unfold. Preliminary examination of the data collected to date shows us that (a) a variety of factors influence teens' perceptions of dating violence (e.g., whether the perpetrator is male or female, a friend or a stranger, gender of respondent), and (b) that teens express approval and disapproval of dating violence in a number of ways. The insights provided by this exercise can be translated into more appropriate and discriminating items that teens will respond to with greater variability.

In addition to considering novel approaches such as this, future assessment development should include evaluation of measurement invariance during instrument construction. Whether the developer wants to exclude variant items or include them and adjust for them in the scoring, this practice will provide important information and will minimize biased inferences about group differences in the construct being measured.

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Table 1. Reference structure correlations from 3-factor EFA solution.

	Factor 1	Factor 2	Factor 3
PN1. Girls sometimes deserve to be hit by boys they date.	0.88		
PN2. Girl who makes boyfriend jealous on purpose deserves to be hit.	0.85		
PN3. OK for boy to hit girlfriend if she did something to make him mad.	0.93		
PN4. OK for boy to hit girlfriend if she insulted him in front of friends.	0.89		
PN6. Sometimes boys have to hit girlfriends to get them under control.	0.80		
PN5. Boys sometimes deserve to be hit by girls they date.	*0.49*	0.57	
NB3. Boy says something bad to girl, OK for her to scream at him?		0.70	
NB4. Boy says something bad to girl, OK for her to hit him?		0.86	
NB5. Boy hits girl, OK for her to hit him back?		0.53	
PN8. It is OK for a girl to hit a boy if he hit her first.		0.54	
PN7. It is OK for a boy to hit a girl if she hit him first.	*0.64*		0.39
NB1. Girl says something bad to boy, OK for him to scream at her?			0.57
NB2. Girl says something bad to boy, OK for him to hit her?			0.54
NB6. Girl hits boy, OK for him to hit her back?			0.73

Note: only coefficients ≥ .30 are included in this table. Items PN5 and PN7 had loadings ≥ .30 on two factors. Their loadings on factor 1 (italicized entries) were ignored.

Table 2. Results of DIF analyses for three factors.

	Test for item DIF (3 *df*)		Test for a DIF (1 *df*)		Test for b DIF (2 *df*)	
<u>Factor 1</u> (PN3 is anchor item)						
Item	-2LL	*p*	-2LL	*p*	-2LL	*p*
PN4	3.6	.463				
PN1	8.4	.078				
PN5	17.5	.001*	4.3	.038	13.2	.004*
PN2	28.9	<.0001*	8.9	.003*	20.0	.0002*
<u>Factor 2</u> (NB3, NB4, PN5 are anchor items)						
Item	-2LL	*p*	-2LL	*p*	-2LL	*p*
PN8	17.9	.001*	3.5	.061	14.4	.002*
NB5	18.5	.001*	3.9	.048	14.5	.002*
<u>Factor 3</u> (NB2, PN7 are anchor items)						
Item	-2LL	*p*	-2LL	*p*	-2LL	*p*
NB1	11.1	.025				
NB4	19.6	.001*	0.5	.48	19.1	.0003*

Note: Asterisks indicate test was statistically significant at $p<.01$ after controlling for multiple tests with the NBenjamini-Hochburg adjustment. –2LL is the –2*loglikelihood value for the nested model comparison and is distributed as χ^2 with the specified *df*.

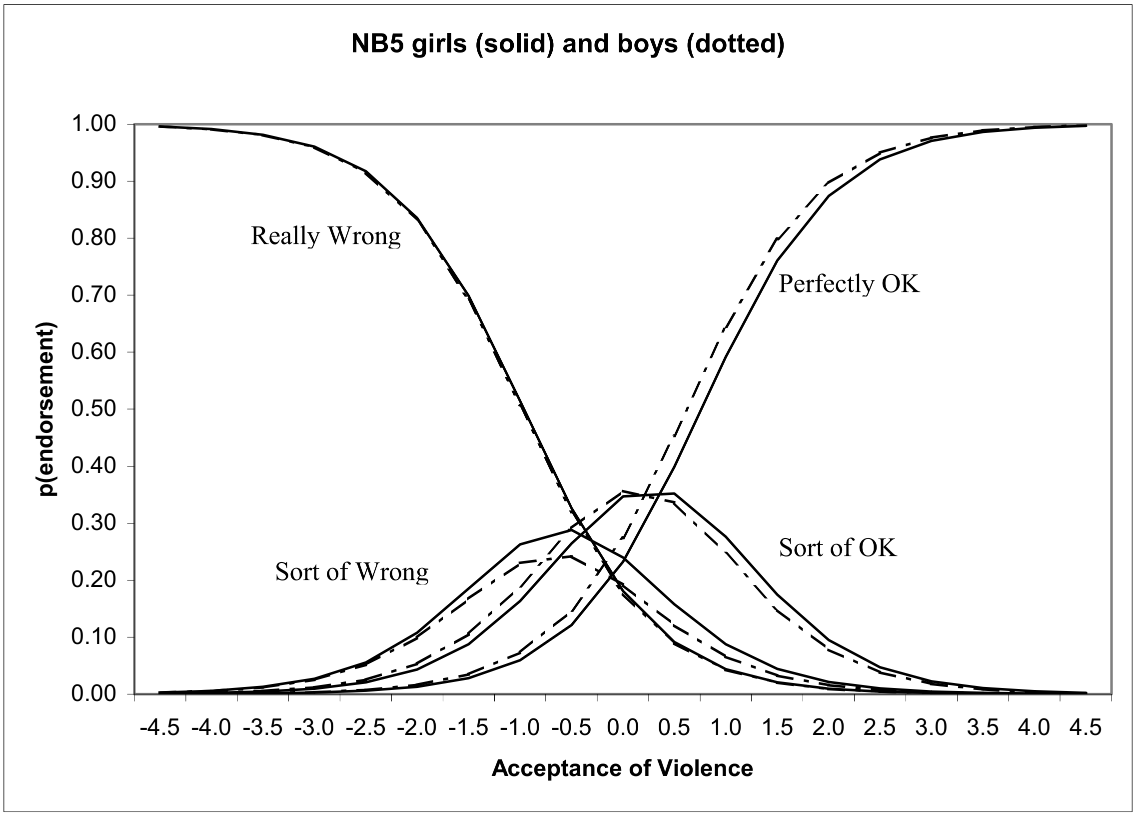
Table 3. Final item parameter estimates and their standard errors for the three factors.

	a	b_1	b_2	b_3
Factor 1				
PN1	2.73 (0.16)	1.08 (0.04)	1.71 (0.07)	2.36 (0.12)
PN3	4.60 (0.31)	1.11 (0.03)	1.72 (0.06)	2.11 (0.09)
PN4	3.79 (0.23)	0.96 (0.03)	1.78 (0.06)	2.16 (0.09)
PN2 – girls	3.47 (0.30)	0.79 (0.05)	1.50 (0.10)	2.14 (0.20)
PN2 – boys	2.75 (0.19)	0.67 (0.04)	1.57 (0.08)	2.26 (0.13)
PN6 – girls	2.38 (0.10)	1.02 (0.06)	1.66 (0.10)	2.46 (0.20)
PN6 – boys	2.38 (0.10)	0.95 (0.05)	1.64 (0.07)	2.36 (0.12)
Factor 2				
NB3	1.27 (0.06)	-1.55 (0.08)	0.53 (0.05)	2.22 (0.11)
NB4	1.91 (0.09)	0.47 (0.04)	1.61 (0.07)	2.62 (0.12)
PN5	1.10 (0.05)	0.36 (0.06)	1.72 (0.11)	3.30 (0.20)
NB5 – girls	1.57 (0.05)	-0.96 (0.06)	-0.20 (0.06)	0.76 (0.06)
NB5 – boys	1.57 (0.05)	-0.98 (0.07)	-0.34 (0.06)	0.62 (0.06)
PN8 – girls	1.72 (0.06)	-0.28 (0.05)	0.68 (0.06)	1.51 (0.08)
PN8 – boys	1.72 (0.06)	-0.25 (0.05)	0.55 (0.06)	1.34 (0.07)
Factor 3				
NB1	0.86 (0.06)	-0.95 (0.09)	2.06 (0.15)	4.64 (0.34)
NB2	1.66 (0.18)	2.53 (0.18)	3.31 (0.28)	3.55 (0.32)
PN7	1.58 (0.09)	0.96 (0.06)	2.16 (0.11)	2.95 (0.17)
NB6 – girls	2.54 (0.10)	0.55 (0.04)	1.40 (0.06)	2.22 (0.12)
NB6 – boys	2.54 (0.10)	0.90 (0.05)	1.72 (0.07)	2.41 (0.12)

Table 4. Boys' and girls' factor means (SD) for 3 different types of scores.

	Boys (N=1265)	Girls (N=1310)	Difference	T-value (prob t)
Factor 1				
Raw Score	6.474 (2.688)	5.706 (1.996)	0.768 (2.359)	8.15 (<.0001)
Non-DIF IRT	-0.038 (0.811)	-0.325 (0.649)	0.287 (0.733)	9.89 (<.0001)
DIF IRT	-0.008 (0.802)	-0.245 (0.637)	0.236 (0.723)	8.26 (<.0001)
Factor 2				
Raw Score	10.190 (3.255)	9.761 (3.230)	0.429 (3.242)	3.32 (.0009)
Non-DIF IRT	-0.015 (0.825)	-0.108 (0.827)	-0.093 (0.826)	-2.84 (.0045)
DIF IRT	-0.004 (0.817)	0.070 (0.834)	-0.065 (0.825)	-2.01 (.0449)
Factor 3				
Raw Score	5.629 (1.728)	5.526 (1.561)	0.103 (1.645)	1.56 (.1185)
Non-DIF IRT	0.090 (0.708)	0.075 (0.694)	0.016 (0.701)	0.56 (.5721)
DIF IRT	0.010 (0.740)	-0.094 (0.691)	0.104 (0.716)	3.69 (.0002)

Figure 1. Girls' and Boys' Category and Item Response Functions for Item NB5 from Factor 2.



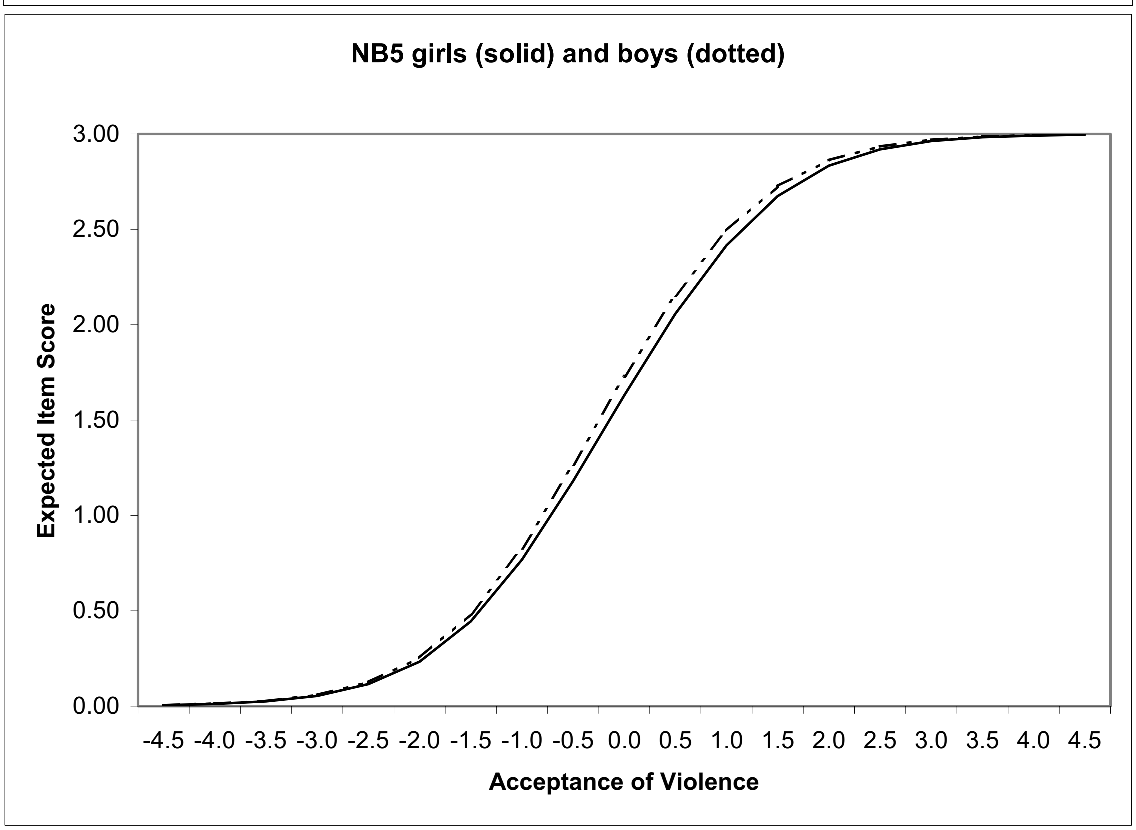
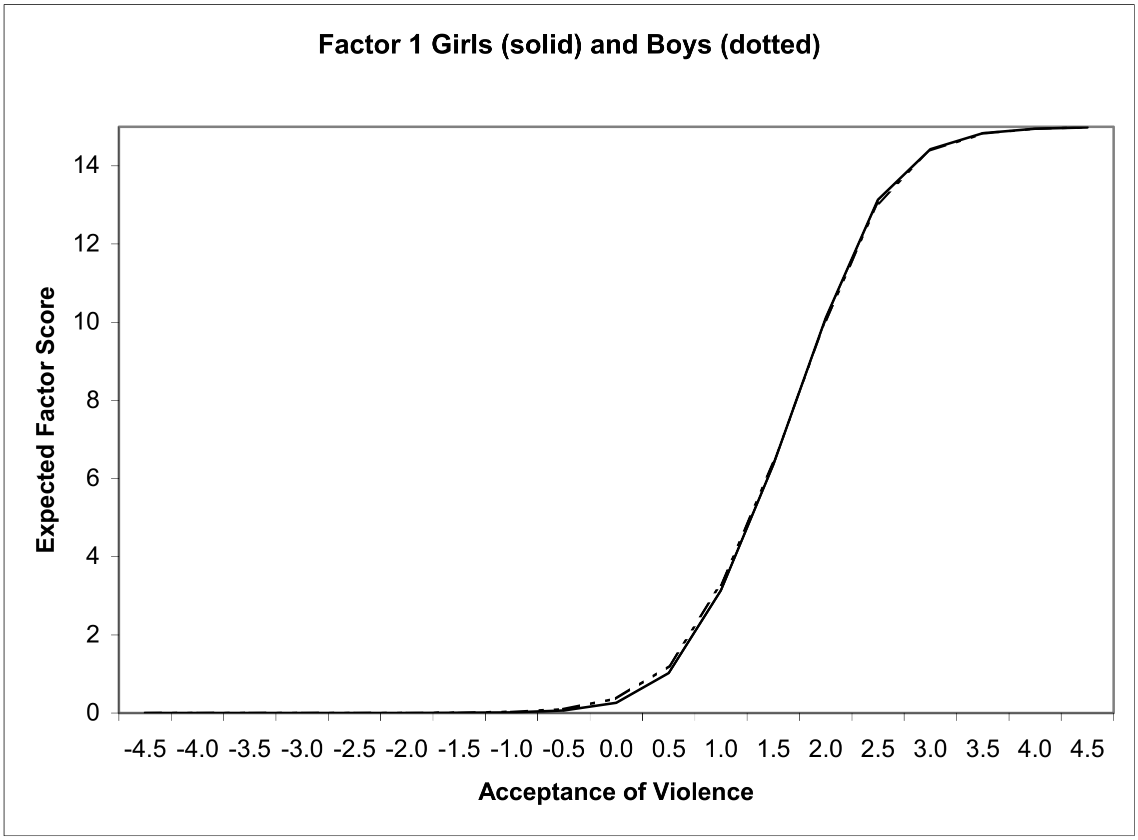
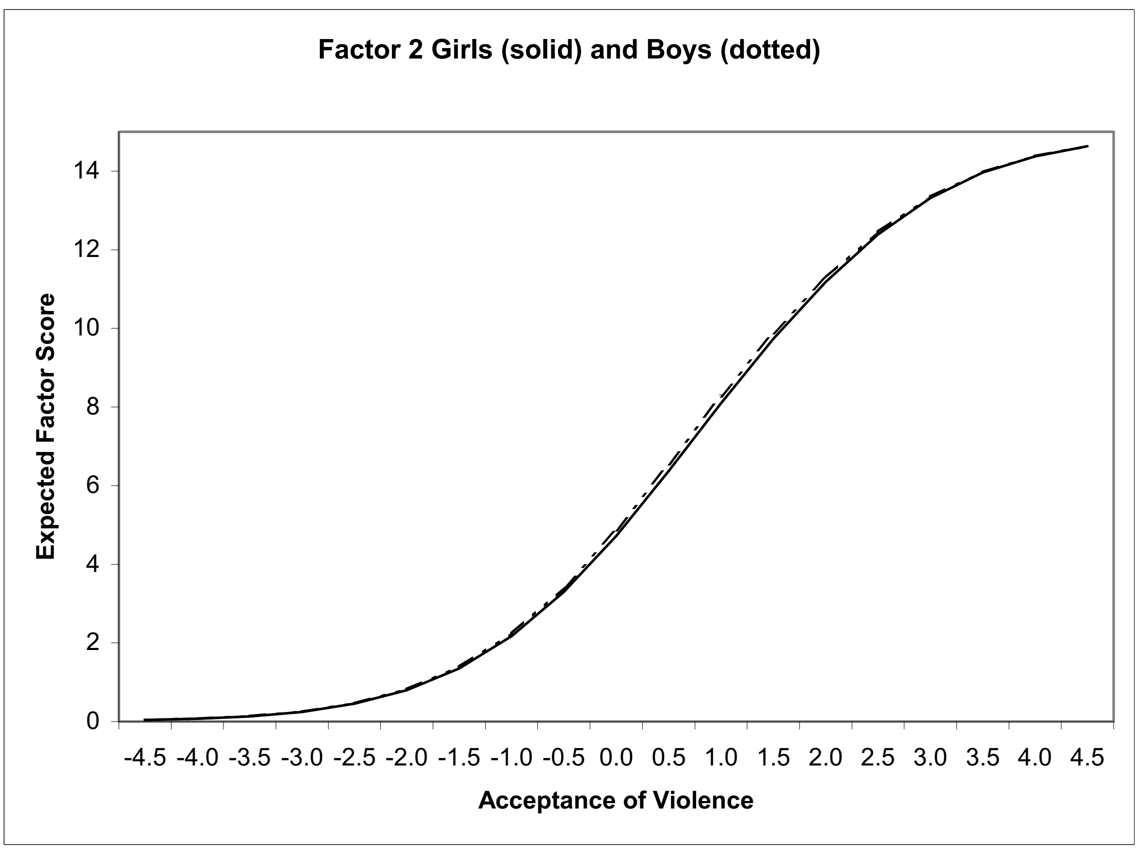


Figure 2. Girls' and Boys' Response Functions for each of the Three Factors.





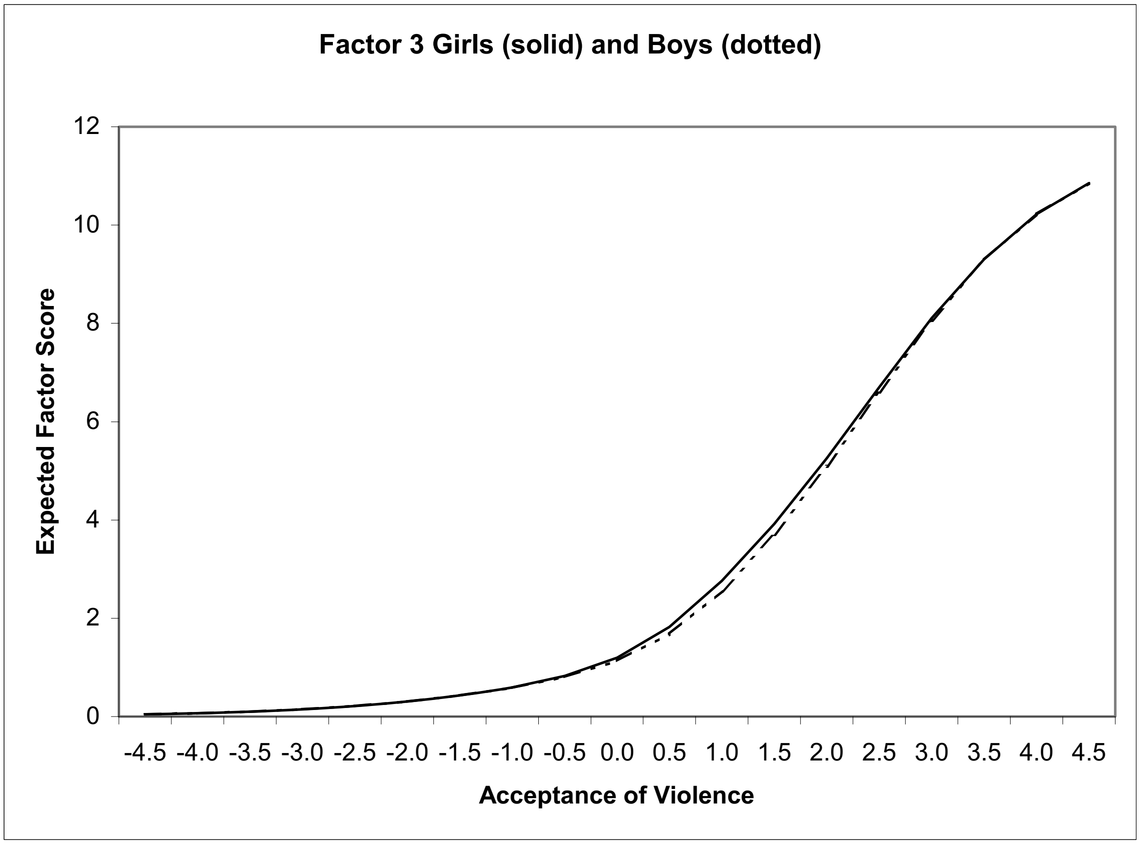

Factor 3 Girls (solid) and Boys (dotted)
Expected Factor Score
0
2
4
6
8
10
12
-4.5 -4.0 -3.5 -3.0 -2.5 -2.0 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5
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Figure 3. Scatterplot of Factor 3 Scale Scores and DIF-adjusted IRT Scores.