Educational and Psychological Measurement
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Educational and Psychological Measurement 1997 57: 785
DOI: 10.1177/0013164497057005004

CORRECTING FOR MEASUREMENT ERROR ATTENUATION IN STRUCTURAL EQUATION MODELS: SOME IMPORTANT REMINDERS

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The increasing popularity of structural equation models that correct for attenuation due to measurement error is noted. The methods by which structural models correct for the effects of measurement error are reviewed. Next, implications of such disattenuation for interpreting the results of structural equation models are considered. Recommendations are advanced for addressing the practice of disattenuation, and caution is urged in drawing inferences based on disattenuated parameter estimates.

Given that "all observation is fallible," variables in the behavioral and social sciences are seldom, if ever, perfectly measured (Duncan, 1975, p. 113). Indeed, in applied areas, measured variables frequently have reliabilities estimated at less than .80 and, not too uncommonly, less than .70 (Williams & James, 1994). Thus, as Cohen and Cohen (1983, p. 407) noted, it is hardly surprising that R^2 values approaching even .50 are scarce, especially when as much as 30% of a criterion's (Y) variance may be subject to the effects of random measurement error and are, by definition, inaccessible to prediction.

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Educational and Psychological Measurement, Vol. 57 No. 5, October 1997 785-799

Measurement

Error due to unreliability poses a special challenge to applied researchers (Clogg, 1992). To the extent that standard techniques of analyses become misleading if measurement error is present, fallible (i.e., unreliable) measures bias relationship estimates between constructs, with subsequent effects on Type I and II errors (Schmidt & Hunter, 1996). This, understandably, reduces the confidence that may be vested in tests of theoretical models.

Although measurement error may also be due to systematic sources, such as errors in scoring or coding, in discussions of reliability (such as that here) the term *measurement error* typically refers to the extent to which random (i.e., unsystematic) error affects measurement of a given variable (see Feldt & Brennan, 1988, for a detailed explanation of reliability theory). As classically conceived, there have been three empirical approaches to estimating the reliability of a measure or process (Pedhazur & Schmelkin, 1991, p. 88): the correlation between scores on the same measure given at different times (the test-retest approach), the correlation between comparable forms of the same measurement (the equivalent forms approach), and the correlation between comparable parts of the same measure (the internal-consistency approach). Of these approaches, the coefficient-alpha formula (Cronbach, 1951) for estimating a measure's internal consistency is probably the most widely used (Peterson, 1994). A technical treatment of the theory underlying coefficient alpha is available in Cortina (1993).

The popularity of the coefficient-alpha formula stems, in part, from the fact that unlike other traditional approaches to estimating reliability, it can be calculated based on a single administration of a single form (Zimmerman, Zumbo, & Lalonde, 1993). Moreover, in a two-variable model, alpha may be used in a "correction" formula to estimate the correlational value (i.e., the disattenuated or "true" degree of association) one would expect if either or both variables were measured without error (i.e., reliability equal 1.00; Bohrnstedt, 1993). Following Spearman (1904), in situations where the correction for attenuation is to be made in both variables, the expected value is estimated by dividing the observed correlation between the variables by the square root of the product of their reliability coefficients (the maximum possible correlation between the imperfectly measured variables). If the correction is to be made in only one of the two variables, the square root of the reliability coefficient for that variable alone would be placed in the denominator. For a historical overview of the correction for attenuation, as well as a review of its applications and interpretations in meta-analysis and validity generalization theory, see Muchinsky (1996).

More recently, a second approach to correcting for attenuation has gained popularity. This approach, stemming from Jöreskog's (1970) pioneering work in structural equation modeling and the associated Linear Structural Relations computer program (LISREL; Jöreskog & Sörbom, 1993), has been rapidly accepted throughout the behavioral and social sciences (Kelloway, 1996). A much-heralded feature of LISREL and other such programs is that they make allowances for less-than-perfect measurement, yielding what are generally considered to be "purified" or "uncontaminated" estimates of the "true" relation between a causal and a response variable (Reuterberg & Gustafsson, 1992). Structural equation models thus permit researchers to study the influence of one "error-free" construct on another, thereby "eliminating" potential bias due to attenuation (Huba & Harlow, 1987).

Although correcting for attenuation was first proposed more than 90 years ago, the appropriateness of adjusting for measurement error remains controversial (Muchinsky, 1996). Advocates maintain that "correction is not only desirable but critical to both accurate estimation of scientific quantities and to the assessment of scientific theory" (Schmidt & Hunter, 1996, p. 199). Critics counter that in an imperfect world there is no such thing as a perfect measure, and that when underestimates of reliability are used, the resulting disattenuated correlation is overestimated, thereby potentially leading researchers into a "fantasy world" (Pedhazur & Schmelkin, 1991, p. 114).

Given these contrasting views, the purpose of the present article is to link the growing structural equation modeling literature to the correction for attenuation literature. In this respect, despite a long history, we are of one with Schmidt and Hunter (1996), who maintain that technical presentations of issues associated with corrections for attenuation have proved inadequate in informing applied researchers of the nuances associated with correcting for measurement error. Moreover, whereas prior presentations have addressed measurement error in other more contemporary analytic procedures (e.g., Carroll & Stafanski, 1994), no prior treatment solely focusing on issues related to corrections for attenuation as applied to structural equation models has been published in this form.

Establishing Causal Priority

Researchers in numerous fields have used structural equation models to deal with error simultaneously in measurement and estimation. Such applications require identifying causal interrelations among all relevant constructs. Several authors, including Bollen (1984), Cohen, Cohen, Teresi, Marchi, and Velez (1990), and Bollen and Lennox (1991), have noted, however, that establishing causal priority in structural equation models can be problematic. Following either classical test theory or factor analysis models, most researchers assume that so-called indicators are "caused" by underlying latent variables. Figure 1(a) presents a simple path diagram incorporating this assumption. As shown, two indicators (x_1 and x_2) are influenced by a latent variable ξ_1. The coefficients associated with each indicator (λ_1 and λ_2) may be viewed as factor weights reflecting the influence

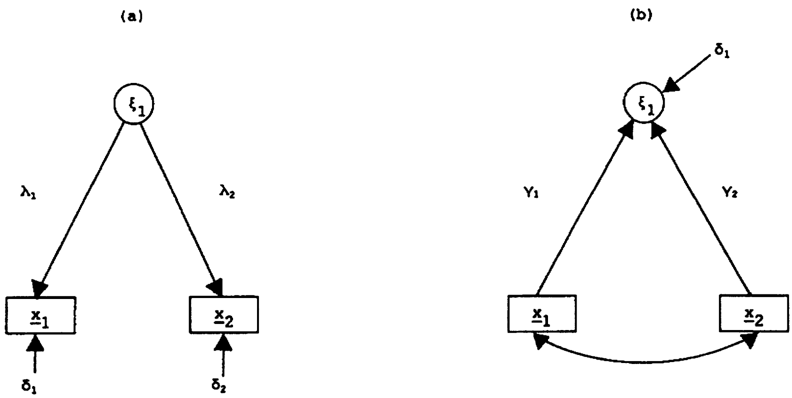


Figure 1. Two alternative measurement models.

within each indicator accounted for by ξ_1. The δ variables represent errors resulting from the imperfect measurement of ξ_1 by x_1 and x_2; essentially residuals, in this theoretical perspective (unlike the classical theory view), these errors may be random or the result of systematic influences not explicitly modeled. The latent variable in Figure 1(a) might be role stress, and the indicators might be four measures of it. Or, ξ_1 could be job performance and the x_is various performance measures.

Although less commonly used, an alternative model may be equally valid. In this model, the causal direction between indicators and latent variables may be reversed. That is, indicators may be viewed as causing latent variables. Figure 1(b) presents a simple path diagram incorporating this perspective. In contrast to Figure 1(a), Figure 1(b) presents two x_i correlated indicators that influence the latent variable, ξ_1. The γ_i coefficients give the association of x_i and ξ_1. If, for instance, ξ_1 represented socioeconomic status, x_i and x_2 might be education and income (Bollen, 1984). A change in education or income is thus expected to alter a person's socioeconomic status, not vice versa.

Discussing the alternative models depicted in Figures 1(a) and 1(b), Bollen and Lennox (1991) and MacCullum and Browne (1993) noted that the models incorporate contrasting implications that result in different conceptions related to the measurement and selection of indicators. For example, causal indicators associated with a given latent variable need not be positively intercorrelated or, stated differently, internally consistent. Thus, whereas an expectation of high positive correlations among indicators in situations analogous to Figure 1(a) would be reasonable, there is no basis to expect high intercorrelations in situations matching Figure 1(b).

In "differentiating between indicators that influence, and those influenced by, latent variables," Bollen and Lennox (1991, p. 305) challenged the conventional notion of reliability. In doing so, they showed that the traditional idea of reliability relating to the consistency (or inconsistency) among several error-prone measurements does not apply for indicators that cause latent variables. Accordingly, the discussion that follows is purposely restricted to situations such as that depicted in Figure 1(a), which is most often the perspective adopted in structural equation modeling.

Disattenuation in Structural Equation Models

As noted, Spearman's (1904) formula for removing error due to attenuation in one of two variables requires dividing their observed correlation by the square root of a focal variable's reliability coefficient. By contrast, structural equation models correct for measurement error by estimating the "true" correlation between a causal and a response variable, for example, X and Y. This is achieved by assuming that all the random error in the indicators underlying X (e.g., x_1, x_2, x_3, x_4) is essentially residual variance, and the correlation between X and Y is estimated free from these residual variances.

To illustrate, within the context of situations in which indicators are viewed as being caused by underlying latent variables (i.e., Figure 1[a]), consider the path diagram in Figure 2. To correct the observed correlation between X and Y for measurement error in X only, the reliability of the composite sum of x_1, x_2, x_3, and x_4 (i.e., X_c) would be estimated using the Spearman-Brown prophecy formula (Cohen et al., 1990, p. 189, Equation 1):

$$r_{X_c X_c} = \frac{k\bar{r}_{ij}}{1 + (k-1)\,\bar{r}_{ij}}, \tag{1}$$

where k is the number of items being added, r is the average correlation across items, and all item standard deviations are assumed equal. Thus, for $k = 4$, as in Figure 2, assuming that the mean correlation across items is .40, the reliability of the composite sum of x_1, x_2, x_3, and x_4 is 4(.4) / 1 + (4 – 1).4 = .727.

The correlation between the composite X_c and Y is then a function of the correlations $\bar{r}_{ij}$ and r_{iy} and k (Cohen et al., 1990, p. 189, Equation 2):

$$r_{X_c Y} = \frac{\sum r_{iy}}{[k + k(k-1)\,\bar{r}_{ij}]^{.5}}. \tag{2}$$

For the above data, assuming $r_{iy} = .2$, the correlation of the composite X_c and Y is $(.2 + .2 + .2 + .2) / (4 + 4[4 - 1][.4])^{.5} = .270$. Correcting this value for attenuation by dividing the correlation between the composite X_c and Y by the square root of the reliability of the composite yields the result $.270 / .727^{.5} = .317$.

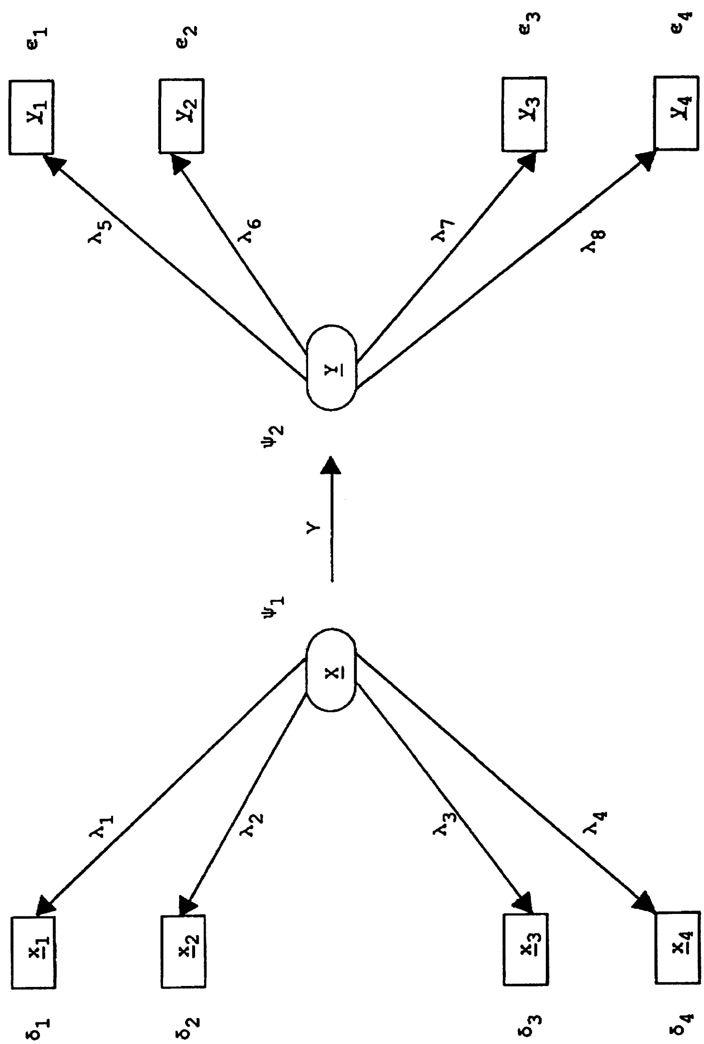


Figure 2. Hypothetical latent variable model.

The similarity between this disattenuation procedure and Spearman's (1904) correction for attenuation formula is apparent (Bagozzi, 1981). In the above instance, as in Spearman's (1904) formula, the causal estimate of X's effect on Y is based on a theoretically perfectly reliable measure of X as contrasted with the imperfect measure that would be the result of a simple linear composite of the indicator variables x_1, x_2, x_3, and x_4.

Implications of Disattenuation

Although the consequences of imperfect measures for the magnitude and form of relationships between variables remain a continuing topic (e.g., Bedrick, 1995; Muchinsky, 1996; Schmidt & Hunter, 1996), the implications of disattenuation for interpreting the results of structural equation models have not yet been sufficiently emphasized. In this regard, first, it should be realized that not all measurement error is independent across variables. Second, it should be understood that structural equation modeling is subject to a range of statistical conditions. Third, it should be appreciated that remedial adjustments for measurement error provide results based on hypothetical rather than obtained data.

Measurement Error Across Variables

Although in structural equation modeling it is commonly hypothesized that errors of measurement associated with indicators are uncorrelated, this is not necessarily always the case, especially in cross-sectional studies (Jöreskog, 1993, p. 314n). If measurement error correlates from one indicator to another, this suggests that the indicators measure "something else" or "something in addition to" the construct they are believed to represent (Jöreskog, 1993, p. 297). Correlations between such error terms must then be critically judged and substantively interpreted to ensure that a construct's meaning and dimensionality are as intended. Such judgments and interpretations are especially complicated in cases where measured variables might be related to a latent variable by means of an unmeasured common cause (Bookstein, 1986, p. 208).

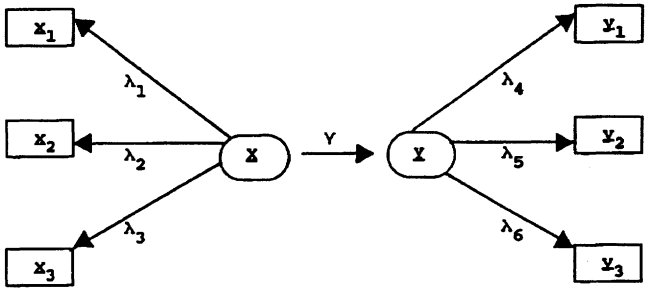
Whereas Anderson and Gerbing (1988) have reviewed the relevant literature for guidance on appropriately operationalizing indicator variables to ensure their fidelity, a related concern centers on the observed correlations among individual causal and response variables. The absolute and relative magnitudes of intercorrelations among a latent variable's indicators not only affect the acceptability of a model (based on goodness-of-fit measures) but also can affect the correlations among a model's other latent variables (Reddy, 1992). This possibility is well-known but is insufficiently considered by some modeling practitioners.

In short, the resulting misspecifications may not only affect effects that might emerge if such correlated errors were not present but also yield effects that appear substantively important yet are merely artifacts of violated statistical assumptions relating to covariation in measurement error (Kessler & Greenberg, 1981, pp. 145-146). Indeed, as shown by Cohen and Cohen (1983, pp. 408-409; Cohen et al., 1990), corrections for attenuation of relationships in multivariable models can result in either increases or decreases in estimated path coefficients, even including changes in sign. Moreover, such estimates may exceed ± 1.00 (i.e., Heywood cases), thus yielding improper solutions (Dillon, Kumar, & Mulani, 1987).

Perhaps the most common result, however, in such situations is artificially inflated parameter estimates (Reddy, 1992). To illustrate this result, we estimated the structural model depicted in Figure 3. All estimates were based on the predicted population covariance matrix per the specified model. Each indicator was arbitrarily assigned a mean of 10 and a standard deviation of 2. Initially (Case A in Figure 3), all correlations between indicators (x_i, y_i) were set to .20. Under these circumstances, the coefficients associated with each indicator (λ_i) equal .45, and parameter estimate (γ) relating X and Y equals 1.00.

In the next three analyses (Cases B through D), the intercorrelations between the y_i indicators were increased to .40, .60, and .80, respectively, with all x_i indicators intercorrelating .20. Given these new circumstances, coefficients associated with individual indicators remain constant within each case, but the parameter estimate (γ) relating X and Y drops dramatically from .71 to .58 to .50.

In essence, the smaller the intercorrelations among y_i indicators, the greater the disattenuation, thereby resulting in larger parameter estimates (γ). Other things equal, when the purpose is to test a proposed structural parameter between X and Y, modelers in Cases A through D are "rewarded" for poor measurement. In all four cases, the resulting parameter estimate (γ) exceeds the intercorrelation of the indicators underlying the proposed latent variables. As shown in Cases E, F, and G, this outcome is symmetrical regardless of which indicators (predictor or criterion) are poorly measured. Whereas structural equation modeling advocates (e.g., Huba & Bentler, 1982) have argued that reliance on latent-variable models is "a great virtue," especially when variables are measured with large amounts of error, critics (e.g., Baumrind, 1983) suggest that, however sophisticated, statistical procedures cannot possibly compensate for poor-quality measurement. This position stresses that, counterarguments concerning allowances for imperfect measurement aside, latent-variable models (like other analytic procedures) equally demand high-quality measures if valid inferences about causal relationships are to be made.



Case A: All rs = .20

λ_1 = .45 λ_4 = .45
λ_2 = .45 λ_5 = .45
λ_3 = .45 λ_6 = .45
γ = 1.00

Case B: rs for y_1, y_2, y_3 = .40

λ_1 = .45 λ_4 = .63
λ_2 = .45 λ_5 = .63
λ_3 = .45 λ_6 = .63
γ = .71

Case C: rs for y_1, y_2, y_3 = .60

λ_1 = .45 λ_4 = .77
λ_2 = .45 λ_5 = .77
λ_3 = .45 λ_6 = .77
γ = .58

Case D: rs for y_1, y_2, y_3 = .80

λ_1 = .45 λ_4 = .89
λ_2 = .45 λ_5 = .89
λ_3 = .45 λ_6 = .89
γ = .50

Case E: rs for x_1, x_2, x_3 = .40

λ_1 = .63 λ_4 = .45
λ_2 = .63 λ_5 = .45
λ_3 = .63 λ_6 = .45
γ = .71

Case F: rs for x_1, x_2, x_3 = .60

λ_1 = .77 λ_4 = .45
λ_2 = .77 λ_5 = .45
λ_3 = .77 λ_6 = .45
γ = .58

Case G: rs for x_1, x_2, x_3 = .80

λ_1 = .89 λ_4 = .45
λ_2 = .89 λ_5 = .45
λ_3 = .89 λ_6 = .45
γ = .50

Figure 3. Causal estimates and corrections for attenuation.
Note. All models estimated assuming M = 10 and SD = 2 for each observed variable. Unless otherwise noted, all correlations between indicators (x_i, y_i) = .20.

Statistical Conditions

Although seldom explicitly stated, the statistical theory underlying structural equation modeling rests on certain assumptions that, if unmet, may yield biased inferences. For example, to obtain true estimates of population coefficients, it is not only necessary to obtain a random or representative sample from a clearly defined universe (Jöreskog, 1993) but also to ensure that the number of cases available for analysis is sufficiently large to gauge the relevance of first-order asymptotic statistical theory. The question of sample-size adequacy in structural equation models has been addressed by several authors (e.g., MacCallum, Browne, & Sugawara, 1996; Marsh & Balla, 1994). In this connection, asymptotically distribution-free statistical techniques are available in Bentler's (1989) structural equation modeling program, known as EQS. With regard to the importance of a specific sampling scheme, the statistical theory underlying structural equation modeling accounts only for sampling error that occurs with the random sampling of a specified population. Descriptions of target populations and sample-selection procedures are noticeably lacking from most structural equation modeling reports. As Jöreskog (1993, p. 30) noted, without both a clearly defined universe and sample-selection scheme, it is difficult to assign meaning to concepts, such as reliability, that can only be defined for measurements on a known population and have a value unique to that population.

More specifically, the less representative or more idiosyncratic a sample is, the more likely it is that inaccuracies in measurement will occur due to chance. In particular, because reliability coefficients are functions of the sample on which they are based, it follows that the reliability coefficients used in correcting a parameter estimate should be based on a generalizable data set (Bobko, 1983). In this respect, a reliability coefficient is valid only when its standard error of measurement is of the same order of magnitude for a chosen population's entire range of scores (Bobko & Rieck, 1980). Whereas correcting for attenuation does statistically correct for measurement error, doing so will not correct for sampling error. Thus, correcting for attenuation cannot enhance a structural model's generalizability.

Hypothetical Versus Obtained Data

A final implication of disattenuation for interpreting the results of structural equation models follows from the character of parameter estimates that take attenuation into account over those that do not (Cohen et al., 1990, p. 192). In this regard, Cohen and Cohen (1983) and Freedman (1991) combined to caution that because parameter estimates corrected for attenuation are based on hypothetical rather than obtained data, they cannot and should not be translated into generalizable empirical claims with purported practical value. Indeed, Cohen and Cohen (1983) advised that because correlations corrected for attenuation are hypothetical, and relatively little is known about the sampling distribution of corrected coefficients (cf. Rogers, 1976), "no significance tests can be computed on their departure from zero or any other value" (p. 69). McNemar (1969) further cautioned that whereas corrected correlations may be theoretically important, they are of little practical value because they cannot be used in prediction equations. He said, pointedly, "the prediction of one variable from another and the accompanying error of estimate must be based on obtained . . . rather than true scores" (p. 171).

In situations where internal consistency is an inappropriate measure of reliability, Cohen et al. (1990), echoing an earlier recommendation advanced by Block (1963), suggested using an external criterion of reliability (based on either a more traditional approach such as test-retest or simply an educated guess by a knowledgeable researcher) to disattenuate parameter estimates. Care, however, should be exercised in using test-retest or split-half reliability estimates for this purpose, because the assumption of randomly distributed error terms may be violated in the case of both techniques (Blalock, 1965). Moreover, Muchinsky (1996) warned that accurate estimates of test-retest reliabilities depend not only on the nature of the variables being measured but also on the time duration in question.

Along these same lines, Won (1982) advised researchers to conduct a "sensitivity analysis" of parameter estimates using plausible upper bound and lower bound reliability values. Doing so cannot only yield insights into the sensitivity of parameter estimates to varying amounts of measurement error (Bollen, 1989, p. 312) but also recognizes that reliabilities are seldom invariant from one application to another. A procedure for estimating confidence bands or intervals for parameters corrected for attenuation has been described by Forsyth and Feldt (1969).

Discussion

The preceding implications have not been enumerated in the sense of depreciating the usefulness of structural equation modeling. To the contrary, care should be taken to distinguish between the limitations and assumptions of structural equation modeling and the manner in which it is applied (Williams, 1995). In this respect, the consequences of interpreting findings based on disattenuated parameter estimates have previously not been sufficiently emphasized.

To the extent that corrections for attenuation are used, modelers have taken diverse positions. At one extreme, Bookstein (1986) argued that, because the correction for attenuation logic used in structural equation models rests on what he considered to be unverifiable assumptions about measurement error, researchers should never inflate parameters associated with latent variables. Occupying a middle ground, Cohen et al. (1990) recommended that researchers routinely report the composite reliabilities of all latent variables. As an estimate of a latent variable's internal consistency, composite reliability is helpful in ascertaining how errorlessly a latent variable is approximated by its designated indicators (Bacon, Sauer, & Young, 1995). Cohen et al. (1990) asserted, and data provided by Gavin and Williams (in press) from the job satisfaction domain confirmed, that it is not uncommon to find latent variables measured with effective reliabilities that would be considered unacceptable in more traditional analyses.

At an opposite extreme from Bookstein (1986), Rosenthal (1984), writing in the context of meta-analysis, suggested that to avoid potential misunderstanding of corrected statistics, both corrected and uncorrected parameter estimates should be presented (p. 30). This suggestion is consistent with the spirit of the American Educational Research Association's *Standards for Educational and Psychological Tests* (1985), in which researchers are advised that if correlation coefficients are corrected for attenuation, "full information" relevant to the correction should be presented (Standard 1.17, p. 17). In accord with both Cohen et al. (1990) and Rosenthal (1984), we likewise recommend that the reporting of the composite reliabilities and effective (i.e., uncorrected) parameter estimates for all latent variables become a standard practice in structural equation modeling.

In this connection, a question periodically faced by structural equation modelers is what to do if composite reliability estimates are below desired levels. The primary operational reason for a low composite reliability estimate is substandard factor weights (i.e., ratio of error to loading may be significant but relatively small) on some or all of a construct's indicator variables. Increasing the overall level of factor parameters will invariably improve both estimates. There are two general possibilities for small factor parameters: (a) construct multidimensionality or (b) random measurement error. A way to potentially improve the magnitude of parameters is to break a latent construct into two or more separate constructs. The preferred approach is based on a theoretical (i.e., content) basis. A less desirable alternative would be to subject the defined indicators to an exploratory factor analysis and respecify the model based on the results. Clearly, however, this latter approach renders exploratory any subsequent modeling effort.

At the same time, if there are only one or two (or many) indicators demonstrating a poor signal-to-noise (i.e., parameter to error) ratio, a modeler may consider dropping only those questionable indicators. However, this requires a sufficient number of measured variables to be done without a loss of ability to ultimately model a construct as a latent variable. One advantage of this approach, though, is that it can improve scale parsimony and provide measurement guidance for future modelers.

Whereas the message of this article may be interpreted as questioning the use of corrected parameter estimates, this has not been our intention. Rather, our purpose has been (a) to link the growing structural equation modeling literature to the correction for attenuation literature so as to inform applied researchers of the nuances associated with correcting for measurement error and (b) emphatically to remind researchers that serious attention must be paid to the measurement components of all structural models. Models are only as good as their measurement components.

Circumstances should dictate whether corrected parameter estimates should be used in interpreting research results (Muchinsky, 1996). If the emphasis of a research effort is on developing and testing theoretical explanations of behavior under ideal conditions, a state free of measurement error then correcting for attenuation should legitimately be the focus of attention

(Schmidt & Hunter, 1996). Conversely, if a researcher is not confident in the quality of the measured variables (i.e., the measurement model), then uncorrected parameter estimates would more properly apply (Muchinsky, 1996).

We encourage both theory-based and applied researchers to devote greater attention to issues associated with correcting for attenuation in structural equation models, as well as to the meaning of the resulting outcomes for both understanding real-world complexities and implementing real-world solutions. Failing to do so may not only jeopardize the credibility of the researchers involved but also result in unintended consequences for subsequent applications and theory building.

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