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Correcting for Indirect Range Restriction in Meta-Analysis: Testing a New Meta-Analytic Procedure

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Using computer simulation, the authors assessed the accuracy of J. E. Hunter, F. L. Schmidt, and H. Le's (2006) procedure for correcting for indirect range restriction, the most common type of range restriction, in comparison with the conventional practice of applying the Thorndike Case II correction for direct range restriction. Hunter et al.'s procedure produced more accurate estimates of both the mean and standard deviation in meta-analysis than the conventional procedure. Even when its key assumption that the effect of selection on a 3rd variable is fully mediated by the independent variable was violated, Hunter et al.'s procedure was still relatively more accurate than the conventional procedure. When applied to data from a previously published meta-analysis, the new procedure yielded results that led to different substantive conclusions.

Keywords: meta-analysis, range restriction correction, measurement error correction, Monte Carlo simulation

Range restriction is a common phenomenon in research data of all kinds and is particularly common in personnel selection and educational research. It occurs when the variance of a variable in a sample is reduced because of preselection or censoring in some way (Ree, Carretta, Earles, & Albert, 1994). Statistics estimated in such a sample are biased estimates of parameters in the unrestricted population. To empirical researchers, the problem of range restriction can be conceptualized as any situation in which researchers are interested in estimating the parameters of variables in one population (unrestricted population; e.g., the applicant population in employment or educational selection research) but have access only to a sample from another population (restricted population; e.g., the incumbent population; Elshout & Roe, 1973).[1]

As early as the beginning of the last century, Pearson (1903), in developing the Pearson product–moment correlation coefficient, noticed problems due to range restriction and discussed possible solutions. Since then, a great number of studies have examined the biasing effect of range restriction (e.g., Alexander, 1988; Dunbar & Linn, 1991; Lawley, 1943; Linn, Harnisch, & Dunbar, 1981; Ree et al., 1994; Sackett & Yang, 2000; Schmidt, Hunter, & Urry, 1976; Thorndike, 1949). It is evident from the literature that range restriction can create serious inaccuracies in empirical research, especially in the fields of employment and educational selection. The most well-known solutions for this problem are the three Thorndike (1949) correction equations.

Thorndike Case II, by far the most widely used correction, is appropriate under the condition of direct range restriction (i.e., selection of subjects is solely based on their scores or rankings on the independent variable). Using the Thorndike Case II formula to correct for the effect of range restriction is relatively simple because it requires only knowledge of (a) the degree of range restriction in the independent variable and (b) the correlation between the variables in the restricted sample. Unfortunately, range restriction is almost always indirect; direct range restriction is rare (Hunter, Schmidt, & Le, 2006; Linn et al., 1981; Thorndike, 1949). Selection typically occurs on a third variable (variable Z) that is correlated with both the variables of interest (X and Y). Thorndike Case III was specifically developed for this situation. The formula for Thorndike Case III allows the correlation between variables X and Y in the unrestricted population to be estimated from

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[1] The restricted population can be considered as a subgroup of the original unrestricted population.

(a) observed intercorrelations between the three variables (*X, Y*, and *Z*) in the restricted sample and (b) the degree of direct range restriction on the third variable *Z*. In practice, however, information on the third variable *Z* is not available because the selection process occurs on a variable or a combination of variables that is not quantified (e.g., recommendation letters, unquantified subjective judgments, or self-selection; Gross & McGanney, 1987; Linn, 1968; Linn et al., 1981; Schmidt, 2002). Consequently, the Thorndike Case III formula can rarely be applied.[2]

The issue of indirect range restriction correction poses a serious problem not only in individual studies but also in meta-analysis. Though indirect range restriction is prevalent, it is rarely possible for meta-analysts to apply the Thorndike Case III formula. Current meta-analysis methods either do not address the problem of range restriction (Hedges & Olkin, 1985; Rosenthal, 1984) or apply the correction method for direct range restriction (Callender & Osborn, 1980; Hunter & Schmidt, 1990; Raju & Burke, 1983). Although it is obvious that the former practice is likely to yield biased estimates of relationships between constructs when range restriction exists in the data, the latter has often been mistakenly believed to satisfactorily solve the problem. This practice implicitly assumes that effects of corrections for direct and indirect range restriction are similar. This assumption has been proven wrong; using the direct range restriction formula to correct for indirect range restriction typically leads to substantial underestimation of the correlations of interest (Linn et al., 1981; Schmidt, 2002; Schmidt, Hunter, & Pearlman, 1981). For example, Hunter et al. (2006) recently showed that this practice results in serious underestimation of the validities of the General Aptitude Test Battery (a measure of general mental ability) in predicting job performance. Thus it is evident that using the inappropriate model for range restriction in meta-analysis can result in biased estimates of relationships between constructs, which may consequently affect substantive research conclusions.

To address this problem, Hunter et al. (2006) derived and presented a new procedure to correct for the effect of indirect range restriction. This procedure can be used to estimate the mean and standard deviation of the true correlations underlying the primary studies included in a meta-analysis in the context of indirect range restriction. The present study has three purposes: (a) to examine the robustness of the new range restriction correction procedure when its key assumption is violated, (b) to use computer simulation to compare the accuracy of the meta-analysis method based on the new indirect range restriction correction procedure with the conventional range restriction correction, and (c) to illustrate the potential implications of using the new method in empirical research by reanalyzing a published meta-analysis.

The New Meta-Analysis Method

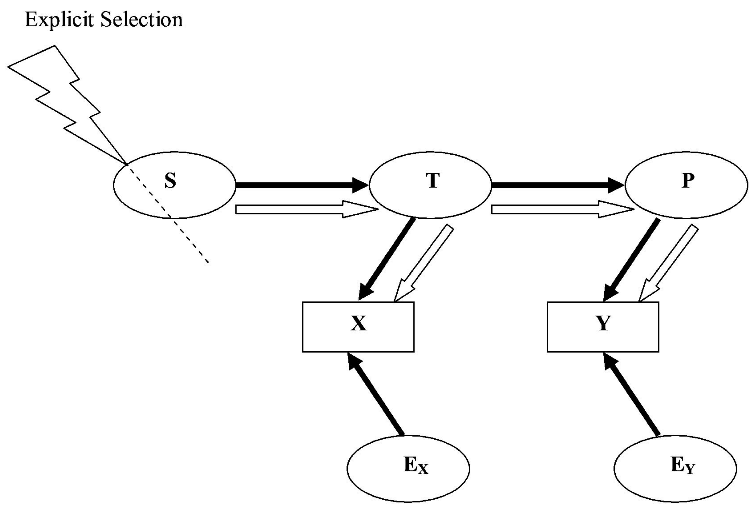
The Structural Model of Range Restriction and Measurement Error

The Hunter et al. (2006) model elaborates on the combined effects of range restriction, measurement error, and sampling error on the observed correlation obtained from a sample drawn from a restricted population. Details of the model and the suggested solution can be found in that study, so only a summary of the method is provided here.

Figure 1 illustrates the model. In the figure, *S* (denoted the *suitability* construct in Hunter et al., 2006) represents the third variable that is correlated with both dependent and independent variables. This variable *S* thus represents the explicit selection variable (*Z*) in the Thorndike Case III formula. It should be noted that *S* may be a composite or a combination of several variables used in selection or determining self-selection (as may occur when people volunteer to participate in a study). Hunter et al. (2006) noted that this model assumes that effects of *S* on the independent variable measure *X* are mediated by the true score *T* of measure *X*. Similarly, it can be seen that the relationship between *X* and *Y* (the observed score of the dependent variable measure) is mediated by *P*, the true score of (construct underlying) *Y*. As shown in Figure 1, explicit selection on *S* causes range restriction on *T*, which then leads to range restrictions on *X* and on *P*. Range restriction on *P* subsequently creates range restriction on *Y*. The key assumption of the model is that there is no arrow directly connecting *S* and *P*; that is, there is no direct effect of *S* on *P*. As described later, this assumption enables estimating the effect of indirect range restriction on the observed correlation between *X* and *Y* in the absence of any information about *S*.

The current model in Figure 1 is in fact a special case of Thorndike Case III in which the path from *S* to *P* is assumed

[2] In practice, selection may occur on more than one variable. This is the situation in multivariate range restriction (Lawley, 1943), which can be seen as a more general case of indirect range restriction where *Z* represents a number of third variables. Procedures for multivariate range restriction correction are available (Lawley, 1943; Ree et al., 1994). However, applying the multivariate range restriction correction requires information about each of the added variables (i.e., variance–covariance matrix of the variables in the unrestricted population), which, just as in the case of indirect range restriction, is rarely available to meta-analysts. So the problem due to indirect range restriction mentioned here can be generalized to cases of multivariate range restriction. As discussed later, to the extent that its basic assumption (i.e., that the effects due to selection on the third variables are fully mediated by the independent variable) is met, the Hunter et al. (2006) procedure can be applied to correct for the effect of multivariate range restriction.



Note: S = The suitability construct where explicit selection occurs.
T = The construct (true score) underlying measure X (independent variable).
X = The observed independent variable.
E_X = Measurement error in X.
P = The construct (true score) underlying measure Y (dependent variable).
Y = The observed dependent variable.
E_Y = Measurement error in Y.
Denotes the structural relationship between variables (no causal relationship is assumed)
Denotes the direction of the effect of range restriction.

Figure 1. The Hunter et al. (2006) model of indirect range restriction.

to be zero. Figure 2 presents the full model of range restriction based on Thorndike Case III. From the tracing rule of path analysis, it can be seen that the assumption of Hunter et al.'s (2006) model is met when the correlation between *S* and *P* (ρ_{SP}) is equal to the product of the path coefficients (correlation coefficients in this case) between *S* and *T* and between *T* and *P*, that is, $\rho_{ST}\rho_{TP}$.

Basic Formulas and Correction Procedures

Symbols

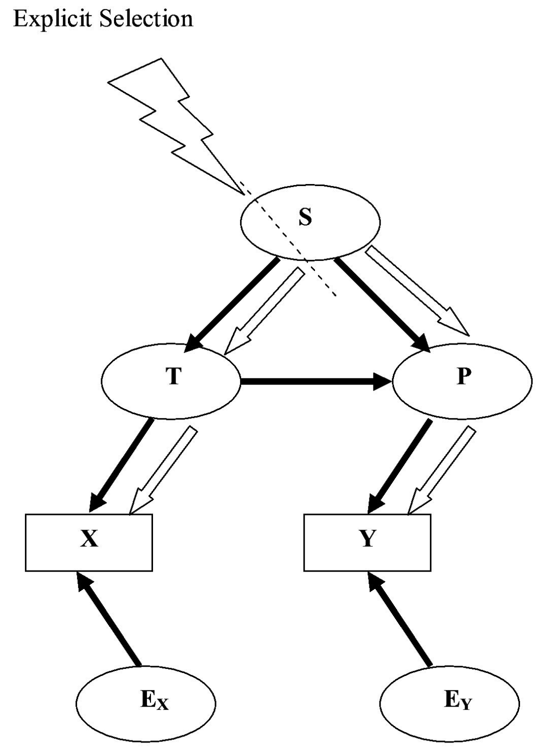
The following symbols are used to present the formulas of the indirect range restriction model: u_S, u_T, u_X, u_P, and u_Y denote the degree of range restriction (i.e., the ratio of standard deviation in the restricted population to that in the unrestricted population) in variables *S, T, X, P*, and *Y*, respectively. Subscript *i* denotes parameters or statistics in the *restricted population*. Subscript *a* denotes parameters or statistics in the *unrestricted population*.[3] The caret symbol (ˆ) is used to indicate estimated statistics, in order to distinguish them from population parameters.

Formulas for the Combined Effects of Range Restriction and Measurement Error

Although range restriction is sometimes present and sometimes not, measurement error is always present in studies because no measures have perfect reliability (Fuller, 1987). Measurement error always acts to create biases in research results that must be corrected, along with the biases caused by range restriction (Callender & Osborn, 1980; Cook et al., 1992; Raju & Burke, 1983; Schmidt & Hunter, 1977). These corrections are needed both in individual studies and in meta-analyses.

Hunter et al. (2006) showed that the correlation between *X* and *Y* in the restricted population is a function of ρ_{TP_a} (correlation between *T* and *P* in the unrestricted population), u_T (range restriction on *T*), ρ_{YY_i} (reliability of the dependent variable measure in the restricted population), and ρ_{XX_i} (re-

[3] For consistency, we adopted the same subscripts used in Hunter et al. (2006), in which *i* stands for job incumbents (representing the common restricted population in personnel selection) and *a* stands for job applicants (representing the common unrestricted population in personnel selection).



Note: S = The suitability construct where explicit selection occurs.
T = The construct (true score) underlying measure X (independent variable).
X = The observed independent variable.
E_X = Measurement error in X.
P = The construct (true score) underlying measure Y (dependent variable).
Y = The observed dependent variable.
E_Y = Measurement error in Y.
⟶ Denotes the structural relationship between variables (no causal relationship is assumed)
⇒ Denotes the direction of the effect of range restriction.

Figure 2. The general model of indirect range restriction.

liability of the independent variable measure in the restricted population):

$$\rho_{XY_i} = \sqrt{\rho_{XX_i}\rho_{YY_i}}\frac{u_T\rho_{TP_a}}{\sqrt{u_T^2\rho_{TP_a}^2 + 1 - \rho_{TP_a}^2}}. \tag{1}$$

The value of u_T in Equation 1 can be obtained from the value of range restriction on X (u_X) and independent variable reliability ρ_{XX_i}:

$$u_T = \sqrt{\frac{\rho_{TX_i}^2 u_X^2}{1 + \rho_{TX_i}^2 u_X^2 - u_X^2}} = \sqrt{\frac{\rho_{XX_i} u_X^2}{1 + \rho_{XX_i} u_X^2 - u_X^2}}, \tag{2}$$

where $\rho_{XX_i} = \rho_{TX_i}^2$ is the reliability of the independent variable X in the restricted population.

Correction Procedure

Estimating the mean true correlation ($\bar{\rho}_{TP_a}$). When information about the artifacts is available in all primary studies in a meta-analysis, correcting for the effects of measurement error and range restriction can be done for each individual study by working backward from Equation 1. Specifically, the correction procedure involves the following steps:

1. Compute $\hat{u}_T$ from $\hat{u}_X$ and $\hat{\rho}_{XX_i}$ using Equation 2 when information on the reliability of the independent variable in a restricted sample $\hat{\rho}_{XX_i}$ is available.

If we instead have information about independent variable reliabilities in the unrestricted population ($\hat{\rho}_{XX_a}$), the reliabilities (ρ_{XX_i}) in the restricted population can first be estimated by the well-known homogeneity formula (Gulliksen, 1950; Hunter et al., 2006):

$$\hat{\rho}_{XX_i} = 1 - \frac{1 - \hat{\rho}_{XX_a}}{\hat{u}_X^2}. \tag{3}$$

2. Estimate ρ_{TP_i} from $\hat{\rho}_{XY_i}$, $\hat{\rho}_{YY_i}$, and $\hat{\rho}_{XX_i}$ using the disattenuation formula:

$$\hat{\rho}_{TP_i} = \frac{\hat{\rho}_{XY_i}}{\sqrt{\hat{\rho}_{YY_i}}\sqrt{\hat{\rho}_{XX_i}}}. \tag{4}$$

3. Apply the Thorndike Case II formula to correct for the effect of range restriction in T:

$$\hat{\rho}_{TP_a} = \frac{\hat{\rho}_{TP_i}}{\sqrt{\hat{u}_T^2 - \hat{\rho}_{TP_i}^2\hat{u}_T^2 + \hat{\rho}_{TP_i}^2}}. \tag{5}$$

Equation 5 requires basic assumptions similar to those required by the Thorndike Case II formula: (a) that the regression line of P on T is linear (linearity assumption) and (b) that the conditional variance of P does not depend on T (homoscedasticity assumption). The mean true score correlation ($\bar{\rho}_{TP_a}$) can then be estimated by taking the weighted mean of the true score correlations obtained in Equation 5 across all primary studies.

The major difference between the new meta-analytic approach and conventional approaches is that the former uses range restriction in the true score (u_T) instead of range restriction in the observed score (u_X) to correct for the effect of range restriction. Because u_T is always smaller than u_X (equality occurs only when the predictor measure is perfectly reliable), the new approach always yields larger estimates for ρ_{TP_a} than those provided by the existing approaches. On the basis of these analytic results, Hunter et al. (2006) suggested that existing meta-analysis methods almost always underestimate the mean true correlation.

Estimating the standard deviation of the true correlation (SD_ρ). When information about range restriction and measure reliabilities is available in all primary studies, the standard deviation of the true correlation (SD_ρ) can be estimated by first correcting each correlation individually and then following relatively simple procedures (Hunter & Schmidt, 2004). When such information is unavailable, artifact distribution meta-analysis must be used, and in that procedure direct estimation of the standard deviation is more complex. Hunter et al. (2006) suggested two alternative approaches based on Equation 1: (a) using the modified interactive approach (cf. Law, Schmidt, & Hunter, 1994) and (b) using a Taylor series approximation approach (cf. Raju & Burke, 1983; Raju, Burke, Normand, & Langlois, 1991). Details of these approaches can be found in Hunter et al. (2006).

Availability of Information About the Artifacts

As evident from the procedure detailed above, the new Hunter et al. (2006) method requires information about the artifacts that affect observed correlations in primary studies. Specifically, to apply the method, one needs information about range restriction on observed scores of the independent variable (u_X), reliabilities of the dependent variable in the restricted population (ρ_{YY_i}), and reliabilities of the independent variables, either in the restricted or unrestricted population (ρ_{XX_i} or ρ_{XX_a}, respectively). As noted earlier, if all primary studies in a meta-analysis report estimates for the artifacts in question, corrections can be performed individually. When information about the artifacts is unavailable or only partially available—a more common situation—corrections can still be made by using artifact distributions constructed from either (a) information about the artifacts derived from similar studies in the literature (cf. Alexander, Carson, Alliger, & Cronshaw, 1989; Pearlman, Schmidt, & Hunter, 1980; Schmidt & Hunter, 1977) or (b) estimates available from the primary studies in the current meta-analysis (Hunter & Schmidt, 1990, 2004). Past simulation studies have shown that meta-analysis methods (based on direct range restriction correction) using artifact distributions provide reasonably accurate estimates of the true correlation distribution as long as the artifact distributions are appropriate (Burke, Raju, & Pearlman, 1986; Callender, Osburn, Greener, & Ashworth, 1982; Law, Schmidt, & Hunter, 1994; Mendoza & Reinhardt, 1991; Raju & Burke, 1983).

Unresolved Issues

As mentioned earlier, several issues should be resolved before the new method can be widely adopted. Below we discuss the issues and explain how they were addressed in this study.

Examining Effects of Violating the Assumption of the Model

The model for indirect range restriction suggested by Hunter et al. (2006) relies on the assumption that the effect of S on the dependent variable P is fully mediated by the independent variable construct T (see Figure 1). Arguably, this assumption is met in selection situations in which a new selection procedure (X as a measure of T) is comprehensive in a sense that it captures the constructs that determine the criterion-related validity (i.e., correlation with P) of the suitability construct (S) on which direct selection has occurred earlier. The assumption, however, may not hold in other situations. Thus, the new procedure may yield biased estimates of the true correlation in such situations. It is even possible that these estimates will be less accurate than those produced by the conventional direct range restriction procedure. In this study, we estimated the bias resulting from using the new procedure when its assumption is violated and compared the bias with that from the conventional correction procedure based on the direct range restriction model. The results from this comparison are relevant to data analysis in both individual studies and in meta-analysis.

Evaluating the Accuracy of the New Method in Meta-Analysis

The new meta-analysis procedure presented in Hunter et al. (2006) is more complicated than previous methods. The basic attenuation formula of the method (Equation 1) is complex and nonlinear, which renders estimating the standard deviation of true correlations (SD_ρ) difficult. Another complicating factor is that the elements in the right side of Equation 1 are not independent of one another. Because both the nonlinear interactive and Taylor series approximation approaches suggest that to estimate SD_ρ, one should assume the elements in the equation are independent, their accuracy may be affected when this assumption is violated. In this study, we simulated data to examine the accuracy of the new meta-analysis method when its basic assumption examined in the previous section is met (i.e., on that basis of the model in Figure 1) across a wide range of conditions for the true parameters (i.e., distributions of true score correlations, reliabilities, and range restriction) and compared the results with those provided by the conventional method based on the direct range restriction correction. The meta-analysis methods examined are based on artifact distribution methods (cf. Hunter & Schmidt, 2004; Hunter et al., 2006; Law et al., 1994), which assume that values of the artifacts (range restriction, reliabilities) are not provided in all the individual studies and only information about their distributions across studies is available. Accuracy in conditions in which different amounts of information about the artifacts are available to researchers was examined.

Illustrating Implications of Using the New Method in Research

The ultimate goal for development of a new analytic method is to apply it to answer substantive research questions. It is therefore important to test the new method on real data to examine its implications, that is, to see if using the new method can lead to conclusions that are substantively different from those reached by the existing meta-analysis methods. Such meaningful differences provide evidence that the new procedure has practical implications for researchers. In this study, we examined this question by reanalyzing a published meta-analysis on the validity of employment interviews (McDaniel, Whetzel, Schmidt, & Maurer, 1994). We selected this study because (a) it addresses an important topic in personnel selection and (b) the studies it is based on are characterized by indirect range restriction.

Method

Examining Effects of Violating the Assumption

Conditions Examined

We examined the potential inaccuracies resulting from violating the assumption of the model by directly calculating the differences between the known true correlation ρ_{TP_a} and those estimated by the new procedure and the earlier correction procedure based on the direct range restriction model under different values of the key parameters involved (i.e., ρ_{ST_a}, ρ_{TP_a}, ρ_{SP_a}, ρ_{XX_a}, ρ_{YY_a}, and u_S). This analysis focused on the correction procedures per se, not on their use in meta-analysis. In this analysis, sample size is infinite, so there is no sampling error, and any differences in results are solely due to the violations of the model assumption. The values of these parameters were chosen to (a) reflect those likely to hold in practice and (b) cover a wide range of all possible values. Specifically, we examined three values of ρ_{ST_a} (.10, .50, and .80, which range from very low to very high correlations between the independent variable and the third variable),[4] three values of ρ_{TP_a} (.20, .40, and 60, typifying small, medium, and large values of the predictor-criterion relationships in personnel selection research), two values of ρ_{XX_a} (.70, which is generally considered acceptable for self-report measures for research purposes, and .90, which is commonly regarded as good for making individual decisions; Nunnally, 1978), two values of ρ_{YY_a} (.50, which is typical for supervisor ratings, and .80, which is typical for work samples), and three values of u_S (.411, .603, and .844, which correspond to the selection ratios of .10, .50, and .90, respectively). For ρ_{SP_a}, we systematically varied its values to manipulate the degree of violation of the assumption. Specifically, the value of ρ_{SP_a} was determined by the following formula:

$$\rho_{SP_a} = \rho_{ST_a}\rho_{TP_a}(1 + k\varepsilon), \qquad (6)$$

where ε was set at .10 and k was varied from 0 to 5 (in units of 1). As discussed in the previous section, when there is no direct path from S to P (i.e., when the assumption of the model is met), on the basis of the tracing rule of path analysis, the correlation between S and P (ρ_{SP_a}) is equal to the product of the paths (correlation coefficients in this case)

[4] In Le (2003), a slightly different set of ρ_{TP_a} values (i.e., .10, .50, and .90) was examined. Because it was realized that the value of .90 might be unrealistically high (i.e., the two constructs S and T would be essentially the same in this case), we decided to change it to .80 in the current study.

between S and T and between T and P, that is, $\rho_{ST_a}\rho_{TP_a}$. Hence the values of ρ_{SP_a} varied from perfectly meeting the assumption (when $k = 0$) up to 150% over that initial value ($k = 5$). We believe that this range of potential violations (i.e., from 0% to 150%) is realistic and covers most situations in practice.

There were a total of 648 sets of comparisons (3 values of $\rho_{ST_a} \times$ 3 values of $\rho_{TP_a} \times$ 2 values of $\rho_{XX_a} \times$ 2 values of $\rho_{YY_a} \times$ 3 values of $u_S \times$ 6 values of k). Our analyses involved four steps: (a) calculating the observed values of the correlation ρ_{XY_i} and other statistical artifacts (u_X, ρ_{XX_i}, ρ_{YY_i}) from the simulation parameters, (b) applying the new approach to estimate the correlation of interest ρ_{TP_a}, (c) applying the conventional approach based on the direct range restriction correction, and (d) comparing results provided by the two methods with the true correlation.

Calculating the Observed Values

For each combination of the simulated parameters, we calculated the values of u_X, ρ_{XX_i}, ρ_{YY_i}, and ρ_{XY_i}. These are the values that are likely to be observed in a primary study in which the two procedures would be used to estimate the true correlation ρ_{TP_a}. (For the conventional approach based on the direct range restriction correction, ρ_{XX_a} and ρ_{YY_a} were assumed to be known because the approach requires such information.) As mentioned earlier, Hunter et al.'s (2006) model is a special case of Thorndike Case III when the path between S and P is zero. So in order to calculate the observed values in general, we made use of the general model underlying Thorndike Case III in which the direct path between S and P exists (see Figure 2). Details of all the calculation steps are described next in the order they were performed.

Calculating u_T. As shown in Figure 2, range restriction on T can be caused by direct range restriction on S. We used Equation 18 from Hunter et al. (2006) to calculate u_T from the available parameters:

$$u_T = \sqrt{\rho_{ST_a}^2 u_S^2 - \rho_{ST_a}^2 + 1}. \tag{7}$$

Calculating u_X. Range restriction on X is directly caused by range restriction on T. Hunter et al.'s (2006) Equation 19 was used here to calculate u_X:

$$u_X = \sqrt{\rho_{XX_a} u_T^2 - \rho_{XX_a} + 1}. \tag{8}$$

Calculating u_P. Range restriction on P is caused by direct range restriction on S. The formula for u_P can be inferred from Equations 7 and 8 by replacing appropriate parameters:

$$u_P = \sqrt{\rho_{SP_a}^2 u_S^2 - \rho_{SP_a}^2 + 1}. \tag{9}$$

Calculating u_Y. Range restriction on Y is directly caused by range restriction on P. We used Hunter et al.'s (2006) Equation 21 to calculate u_Y:

$$u_Y = \sqrt{\rho_{YY_a} u_P^2 - \rho_{YY_a} + 1}. \tag{10}$$

Calculating ρ_{XX_i}. Here, Equation 3 was used to compute ρ_{XX_i} from ρ_{XX_a}:

$$\rho_{XX_i} = 1 - \frac{1 - \rho_{XX_a}}{u_x^2}. \tag{11}$$

Calculating ρ_{YY_i}. As in the case of ρ_{XX_i} above, ρ_{YY_i} was also calculated using Equation 3:

$$\rho_{YY_i} = 1 - \frac{1 - \rho_{YY_a}}{u_Y^2}. \tag{12}$$

Calculating ρ_{TP_i}. From the Thorndike Case III formula, Le and Schmidt (2003) derived a formula that shows ρ_{TP_i} as a function of ρ_{TP_a}, ρ_{ST_a}, ρ_{SP_a}, and u_T:

$$\rho_{TP_i} = \frac{\rho_{TP_a} - (1 - u_T^2)V}{u_T\sqrt{1 - (1 - u_T^2)V^2}}, \tag{13}$$

where $V = \rho_{SP_a}/\rho_{ST_a}$. Equation 13 was used to compute ρ_{TP_i}.

Calculating ρ_{XY_i}. Finally, the values of ρ_{XX_i} and ρ_{YY_i} obtained in previous steps were used to attenuate ρ_{TP_i} in order to compute ρ_{XY_i}:

$$\rho_{XY_i} = \rho_{TP_i}\sqrt{\rho_{XX_i}\rho_{YY_i}}. \tag{14}$$

Applying the New Procedure to Estimate ρ_{TP_a}

The procedure detailed in the previous section was used to estimate ρ_{TP_a} from u_X, ρ_{XX_i}, ρ_{YY_i}, and ρ_{XY_i}. Specifically, Equations 4 and 5 were used.

Applying the Conventional Correction Procedure Based on Direct Range Restriction

Reliabilities of X and Y in the unrestricted population (ρ_{XX_a} and ρ_{YY_a}) were used together with u_X and ρ_{XY_i} to estimate ρ_{TP_a} by the following equation (Callender & Osburn, 1980):

$$\rho_{TP_a} = \frac{\rho_{XY_i}}{\sqrt{\rho_{XX_a}\rho_{YY_a}(u_X^2 - u_X^2\rho_{XY_i}^2 + \rho_{XY_i}^2)}}. \tag{15}$$

Comparisons

Results obtained by the two methods were compared with the true correlation ρ_{TP_a}. Biases are presented as a percentage of the difference between estimated correlation $\hat{\rho}_{TP_a}$ and the true value ρ_{TP_a}:

$$B\% = 100\,\frac{\hat{\rho}_{TP_a} - \rho_{TP_a}}{\rho_{TP_a}}. \tag{16}$$

Evaluating Accuracy of the New Method Via Monte Carlo Simulation

Conditions Simulated

True score correlation distributions ρ_{TP_a}. Following Law et al. (1994), we examined three different cases of the true correlation distributions. Under each case, there were three different distributions. Case 1 follows the fixed-effects model; that is, there is no variation in the true correlation in the population ($SD_\rho = 0$). Three values of ρ_{TP_a} were examined: .30, .50, and .70 (Distributions 1, 2, and 3, respectively). Case 2 was based on the distributions that Law et al. (1994) deemed realistic in personnel selection research (Distributions 4, 5, and 6). Finally, Case 3 includes the three distributions of true correlations that were originally examined in the Callender and Osburn (1980) Monte Carlo simulation (Distributions 7, 8, and 9). Figure 3 shows the distributions in Cases 2 and 3.

Reliability distributions. The distributions of reliabilities for independent variable and dependent variable measures in the *unrestricted population* originally suggested by Pearlman et al. (1980) were used in the study. The distributions are shown in Figure 4. These distributions were used in many previous meta-analyses (e.g., Gaugler, Rosenthal, Thornton, & Bentson, 1987; Schmidt, Gast-Rosenberg, & Hunter, 1980; Vinchur, Schippmann, Switzer, & Roth, 1998) as well as simulation studies (e.g., Callender & Osburn, 1980; Law et al., 1994; Raju & Burke, 1983).

Here, it is important to caution about the common use of the generalized artifact distribution of unrestricted dependent variable reliabilities ρ_{YY_a} in past research. This distribution for dependent variable reliabilities was empirically constructed on the basis of information available in many validation studies (Pearlman et al., 1980; Schmidt & Hunter, 1977). Because measures of the dependent variable, job performance ratings, could be obtained only from incumbents, reliabilities reported in the literature are *restricted* dependent variable reliabilities ($\hat{\rho}_{YY_i}$). Accordingly, the generalized artifact distribution of ρ_{YY} (Pearlman et al., 1980; Schmidt & Hunter, 1977) should have been considered to represent the reliabilities of dependent variables in the *restricted population* ρ_{YY_i}, not in the unrestricted population as commonly assumed in past research. This consideration may have some implications for accuracies of effect sizes estimated in past research (Sackett, Laczo, & Arvey, 2002). However, in the present study, to ensure that results are comparable to those of past studies (e.g., Callender & Osburn, 1980; Law et al., 1994), we used the generalized artifact distribution for dependent variable reliabilities suggested by Pearlman et al. (1980) as the *unrestricted* ρ_{YY_a} distribution to simulate data.

Range restriction distribution. To make our study comparable to previous simulations, we chose to use the well-known distribution of u_X originally suggested by Pearlman et al. (1980). This requirement added an additional level of complexity to the study because we needed the distribution of u_T underlying the distribution of u_X in order to generate data for our simulations. From Equation 8, a formula can be derived to estimate $\hat{u}_T$ from $\hat{u}_X$ and $\hat{\rho}_{XX_a}$:

$$\hat{u}_T = \sqrt{\frac{\hat{u}_X^2 + \hat{\rho}_{XX_a} - 1}{\hat{\rho}_{XX_a}}}. \tag{17}$$

Although Equation 17 can easily be applied if one has the values of $\hat{u}_X$ and $\hat{\rho}_{XX_a}$ for every primary study in the meta-analysis, creating a distribution of u_T from the distributions of u_X and ρ_{XX_a} is less straightforward. We cannot simply combine all the values of u_X and ρ_{XX_a} in their respective distributions because u_X and ρ_{XX_a} are actually not independent, as shown in Equation 8.

Thus, a special iterative procedure was developed to construct the u_T distribution from the original u_X and ρ_{XX_a} distributions. Appendix A provides details of the procedure. The resulting distribution of u_T used in the study is illustrated in Figure 5.

Simulation Procedure

For each simulation condition, data for 500 meta-analyses (replications) were simulated. As in Law et al. (1994), each meta-analysis included k primary studies, with k being a number randomly selected from 30 to 100. Each study has N "subjects," with N being a number randomly selected from 70 to 150. For each meta-analysis in a simulation condition, parameters of a primary study (u_T, ρ_{TP_a}, ρ_{XX_a}, and ρ_{YY_a}) were randomly drawn from the respective distributions of the condition. Data were then simulated for each subject in the primary study on the basis of the parameters. A program in SAS language was written that enabled such simulation.[5]

Availability of Information in the Primary Studies

For each simulation condition, we varied the extent to which information about the artifacts was available in the primary studies in order to thoroughly examine performance of the new method under different conditions that empirical researchers are likely to encounter in practice. Four conditions of information availability were examined. In all the conditions, it was assumed that the primary studies provide reliability estimates of the dependent variable ($\hat{\rho}_{YY_i}$) to be

[5] This program is available from Huy Le upon request.

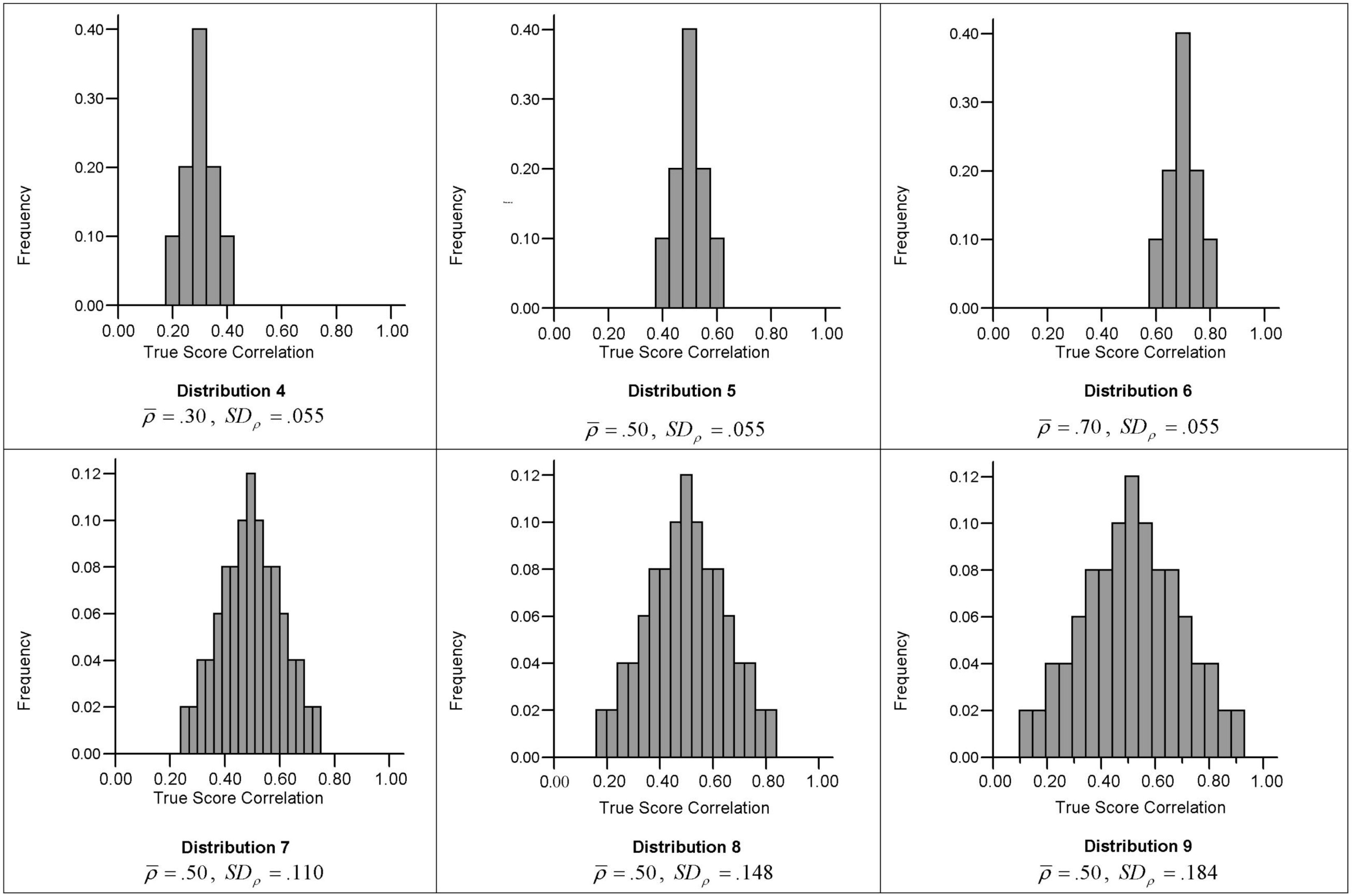


Figure 3. Distributions of the true score correlations ρ_{TP_a} used to simulate data (Distributions 1–3 for the fixed-effects model are not shown here).

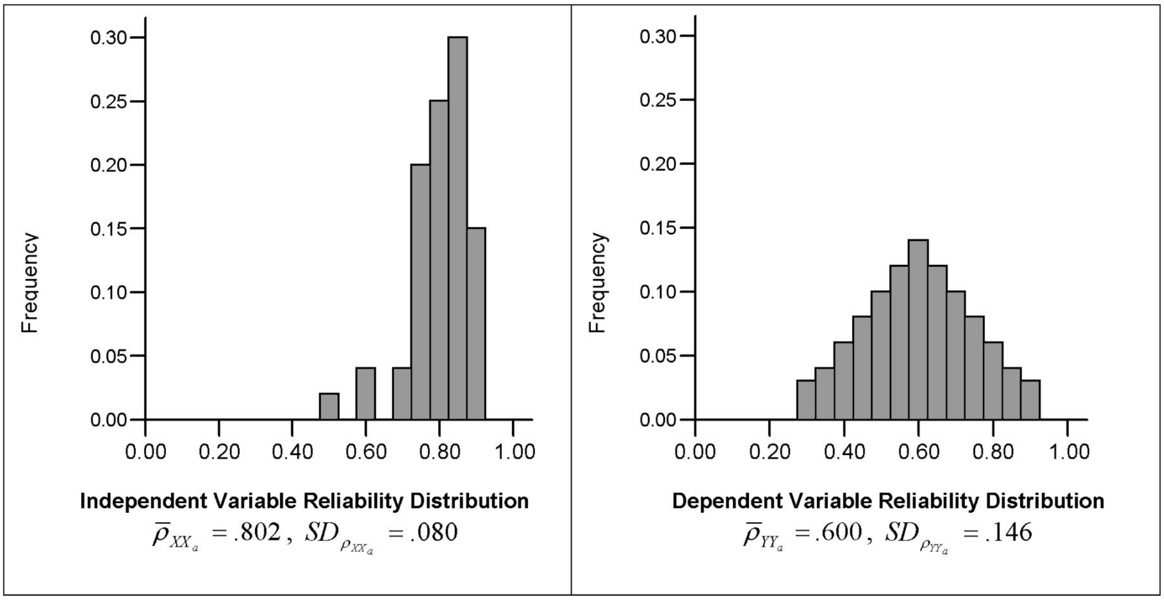


Figure 4. Distributions of reliabilities used to simulate data (ρ_{XX_a} and ρ_{YY_a}).

used in the meta-analysis. As such, information regarding dependent variable reliabilities was sample based (i.e., based on samples of the primary studies included in each specific meta-analysis). This assumption is based on the fact that it is practically impossible to observe the unrestricted dependent variable reliabilities ($\hat{\rho}_{YY_a}$). Compared with previous simulations that unrealistically assumed the unrestricted dependent variable reliabilities were known (e.g., Law et al., 1994; Raju & Burke, 1983), the current study arguably reflects situations that researchers are more likely to encounter in practice. The proportion of the primary studies in a meta-analysis providing the information of dependent variable reliabilities is different across the conditions. Further, the conditions differ in the extent to which information about range restriction and independent variable reliabilities is available to researchers. Details of the conditions are described below.

Condition 1. Here, it was assumed that the true artifact distributions underlying the data (i.e., the distributions of independent variable reliabilities in the unrestricted population ρ_{XX_a} and range restriction on T [u_T] used to simulate the data) are known by researchers. In addition, we assumed that the restricted dependent variable reliabilities ($\hat{\rho}_{YY_i}$) can be estimated in all the primary studies. This condition is similar to those used in most previous simulation studies (e.g., Callender & Osburn, 1980; Law et al., 1994; Raju & Burke, 1983) in which the generalized artifact distributions (u_X, ρ_{XX_a}, and ρ_{YY_a}) were assumed known.[6]

Condition 2. In this condition, we assumed that 50% of the primary studies included in a meta-analysis provide information on independent variable reliability ($\hat{\rho}_{XX_i}$) and range restriction on X ($\hat{u}_X$). Further it was assumed that such information comes from the same set of primary studies (matched condition), so that range restriction on the true score T ($\hat{u}_T$) can be estimated from Equation 17 in 50% of the individual primary studies. In contrast to Condition 1, here information about dependent variable reliabilities ($\hat{\rho}_{YY_i}$) was assumed to be available in only 18 primary studies. That means between 18% (for $k = 100$) to 60% (for $k = 30$) of the primary studies in a meta-analysis provide information needed to construct the distribution of the dependent variable reliabilities. This condition reflects situations that researchers often encounter in practice, where information about the artifact distributions is not always available in every primary study.

Condition 3. Under this condition, information about range restriction ($\hat{u}_X$) and restricted independent variable reliability $\hat{\rho}_{XX_i}$ is available in 50% of the primary studies, but this information does not come from the same studies (i.e., one group of studies provides information about range restriction $\hat{u}_X$, and the other group provides information about $\hat{\rho}_{XX_i}$). As in Condition 2, dependent variable reliabilities ($\hat{\rho}_{YY_i}$) are available in only 18 primary studies in a meta-analysis. Arguably, this unmatched condition is the most common one in practice.

[6] However, in contrast to previous simulation studies, in the present study we assumed that information about dependent variable reliabilities is sample based; that is, they were obtained from the range restricted samples of the primary studies. As noted earlier, this condition is more realistic than those assumed in the previous studies.

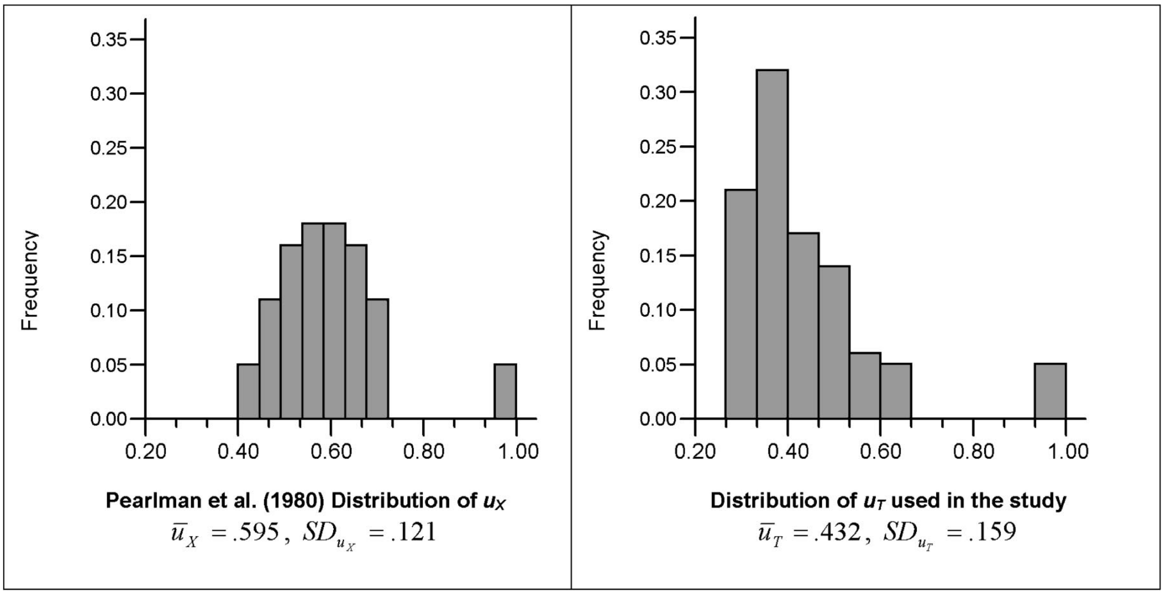


Figure 5. Distributions of range restriction on independent variable observed score (u_X) and true score (u_T) used to simulate data.

Condition 4. This condition was included to examine performance of the direct range restriction method when it is inappropriately applied to indirectly restricted data. The information available for use in the correction for direct range restriction is equivalent to that in Condition 1. That is, in Condition 4, it was assumed that information about the generalized artifact distributions for unrestricted independent variable reliability (ρ_{XX_a}) and range restriction on X (u_X) underlying the data are available. Further, all the primary studies in a meta-analysis provide information on dependent variable reliabilities ($\hat{\rho}_{YY_i}$). Up to now, such information has been sufficient to apply existing meta-analysis methods based on direct range restriction. The interactive range restriction method based on the direct range restriction correction, the currently most accurate meta-analysis method under conditions of direct range restriction (Law et al., 1994), was used to analyze data in this condition. Thus, comparing results obtained in Condition 1 (based on the new method) with those in Condition 4, in which the conventional direct range restriction method was applied, provides a direct test for the accuracy of the new method vis-à-vis current meta-analysis methods and sheds light on the extent of inaccuracies due to inappropriate use of methods based on direct range restriction when range restriction is actually indirect.

Analysis

For Conditions 1–3, the new meta-analysis method for indirect range restriction was applied to analyze data. We used two alternative approaches of the new method: the modified interactive approach and the Taylor series approximation approach (Hunter et al., 2006). For Condition 4, only the interactive nonlinear meta-analysis method based on direct range restriction (Law et al., 1994) was used. Details of the methods are provided in Hunter et al. (2006) and Hunter and Schmidt (2004). We describe only the major steps for each method below.

Indirect range restriction method—Interactive approach. The approach is similar to the existing interactive meta-analysis method (Hunter & Schmidt, 2004). Basically, there are two stages to correct for the effects of artifacts in this meta-analysis approach (Law et al., 1994; Schmidt et al., 1980). The first stage estimates a hypothetical distribution of the observed correlations that would obtain if (a) all the artifacts (measurement error in the dependent variable and independent variable measures and range restriction in the independent variable) are fixed at their mean values and (b) there is no sampling error (Hunter & Schmidt, 2004). The second stage corrects this distribution for the downward biasing effects of range restriction and measurement error to estimate the mean true correlation ($\bar{\rho}$) and its variability (SD_ρ). Further details of this approach are presented in Appendix B.

Indirect range restriction method—Taylor series approximation approach. The approach is modeled after Raju and Burke (1983), with some modifications. Hunter et al. (2006) provided formulas and procedures for applying this approach to corrections for indirect range restriction. Specifically, the mean true score correlation $\bar{\rho}_{TP_a}$ is estimated by correcting the mean observed correlation using the mean of each artifact distribution following the procedure described earlier (Equations 2, 4, and 5). This estimation procedure is different from that used by the interactive procedure. Calculation of the standard deviation SD_ρ is based on the following equation (Equation 31 in Hunter et al., 2006):

$$\rho_{XY_i} = q_{Y_i}\frac{u_T q_{X_a}}{\sqrt{u_T^2 q_{X_a}^2 + 1 - q_{X_a}^2}}\frac{u_T \rho_{TP_a}}{\sqrt{u_T^2 \rho_{TP_a}^2 + 1 - \rho_{TP_a}^2}}, \quad (18)$$

where $q_{Y_i} = \sqrt{\rho_{YY_i}}$ = square root of reliability of the dependent variable Y in the restricted population and $q_{X_a} = \sqrt{\rho_{XX_a}}$ = square root of reliability of the independent variable X in the unrestricted population.

Equation 18 shows the observed correlation ρ_{XY_i} as a nonlinear function of four variables: q_{X_a}, q_{Y_i}, u_T, and ρ_{TP_a}. If these variables can be assumed to be independent, the multivariate Taylor series approximates the nonlinear function with a multivariate polynomial.[7] The first level of approximation is a linear function of the four parameters.[8] Accordingly, the variance of the nonlinear function can approximately be decomposed into four variance components:

$$\mathrm{Var}(\rho_{XY_i}) = b_1^2\mathrm{Var}(q_{X_a}) + b_2^2\mathrm{Var}(q_{Y_i}) + b_3^2\mathrm{Var}(u_T) + b_4^2\mathrm{Var}(\rho_{TP_a}) + \mathrm{Var}(e), \quad (19)$$

with b_1 = first order partial derivative of ρ_{XY_i} with respect to q_{X_a}; b_2 = first order partial derivative of ρ_{XY_i} with respect to q_{Y_i}; b_3 = first order partial derivative of ρ_{XY_i} with respect to u_T; b_4 = first order partial derivative of ρ_{XY_i} with respect to ρ_{TP_a}; and $\mathrm{Var}(e)$ = sampling error variance of $\hat{\rho}_{XY_i}$.

Solving Equation 19 for $\mathrm{Var}(\rho_{TP_a})$, we obtain the formula estimating the desired variance of true score correlations:

$$\mathrm{Var}(\rho_{TP_a}) = [\mathrm{Var}(\rho_{XY_i}) - \{b_1^2\mathrm{Var}(q_{X_a}) + b_2^2\mathrm{Var}(q_{Y_i}) + b_3^2\mathrm{Var}(u_T) + \mathrm{Var}(e)\}]/b_4^2. \quad (20)$$

Taking the square root of Equation 20, we have the standard deviation of the true score correlation (SD_ρ). Hunter et al. (2006) provided formulas for the derivatives and proofs of the derivations.

The interactive meta-analysis approach based on direct range restriction. This analysis is based on the interactive method described in Law et al. (1994). However, because it is assumed that only information about restricted dependent variable reliabilities $\hat{\rho}_{YY_i}$ are available (whereas Law et al., 1994, assumed the unrestricted dependent variable reliabilities ρ_{YY_a} were known), the order of correction had to be modified. Details of the modification are explained in Hunter et al. (2006). The whole correction process can be summarized by the following equation:

$$\hat{\bar{\rho}}_{TPo} = \frac{\hat{\bar{U}}_X\hat{\bar{\rho}}_{XY_i}}{[\hat{\bar{\rho}}_{XX_a}(\hat{\bar{\rho}}_{YY_i} + \hat{\bar{U}}_X^2\hat{\bar{\rho}}_{XY_i}^2 - \hat{\bar{\rho}}_{XY_i}^2)]^{\frac{1}{2}}}, \quad (21)$$

with $\hat{\bar{\rho}}_{TP_a}$ = the mean true score correlation estimate in the unrestricted population, $\hat{\bar{\rho}}_{XY_i}$ = the mean observed correlation in the restricted sample, $\hat{\bar{U}}_X = 1/\hat{\bar{u}}_X$, $\hat{\bar{u}}_X$ = the mean estimate of range restrictions on X, $\hat{\bar{\rho}}_{YY_i}$ = the mean dependent variable reliability estimate in the restricted sample, and $\hat{\bar{\rho}}_{XX_a}$ = the mean independent variable reliability estimate in the unrestricted population.

The interactive procedure as described earlier can be applied to estimate the standard deviation SD_ρ. The range restriction distribution used in the above analysis is the artifact distribution for u_X shown in Figure 3 corresponding to the u_T distribution used to simulate the data.

For each simulation condition, seven analyses were carried out (six for the two approaches based on the new meta-analysis method in Conditions 1–3 and one for the conventional interactive method based on direct range restriction in Condition 4). Results provided by each analysis were averaged across 500 replications. These averages were then compared across analyses.

Reanalyzing a Published Meta-Analysis

The McDaniel et al. (1994) Meta-Analysis

In their comprehensive meta-analysis of employment interviews, McDaniel et al. (1994) estimated the mean validity of interviews (corrected for range restriction and measurement error in the dependent variable measures) at .37. Interview structure was found to be the major moderator, with structured interviews having higher validity (.44) than unstructured interviews (.33). McDaniel et al. (1994) used Hunter–Schmidt's interactive meta-analysis method, which used the model of direct range restriction. The researchers used the sample-based range restriction distribution and (restricted) independent variable reliability distribution in their meta-analysis. To correct for measurement error in the dependent variable (job performance), they used the Pearlman et al. (1980) distribution of unrestricted dependent variable reliabilities ρ_{YY_a}.

In light of the recent findings on the effects of indirect range restriction discussed thus far (Hunter et al., 2006; Sackett et al., 2002), the McDaniel et al. (1994) analysis

[7] It can be seen that q_{Y_i} is not independent of u_T. Thus, the independence assumption for the model is violated. Nevertheless, it is expected that the violation will not seriously affect the accuracy of the estimation (cf. Raju, Anselmi, Goodman, & Thomas, 1998).

[8] We used only the first derivatives of the variables because (a) adding higher order derivatives would make the calculation much more complicated and (b) past research showed that linear equations based on first derivatives could provide reasonably accurate estimates (Raju & Burke, 1983; Raju et al., 1991).

appears to have two methodological problems: (a) Range restriction in the primary studies included in the meta-analysis is indirect, and (b) the Pearlman et al. (1980) generalized artifact distribution for dependent variable reliabilities was actually derived from the restricted population instead of from the unrestricted one.

Range Restriction

Most validation studies for interviews used incumbents. As such, samples of the studies came from the restricted population. Even in rare situations in which applicants were used, such samples of applicants were hired on the basis of other selection procedures. Thus, the effect of range restriction is mostly or entirely indirect. Consequently, the validities of employment interviews estimated in McDaniel et al.'s (1994) study were downwardly biased.

Reliabilities of the Job Performance Rating Criterion

As discussed earlier, the artifact distribution of dependent variable reliabilities commonly used in previous research actually included reliabilities for the restricted population of job incumbents (ρ_{YY_i}), not the unrestricted one (ρ_{YY_a}). Using values of restricted independent variable reliabilities as if they were estimated for the unrestricted population could result in slight overestimation of the true validities of interviews.

The combined effects due to the two problems discussed above can partially offset each other. However, this fact does not justify use of a conceptually inappropriate analytical method. Further, it is important to directly examine the extent and direction of the bias by estimating the true validities using the more appropriate analysis.

Reanalysis

We reanalyzed McDaniel et al.'s (1994) data using the new Hunter et al. (2006) meta-analysis method based on the indirect range restriction correction described earlier. Comparing results of this analysis with those originally reported in McDaniel et al. (1994) should provide information on whether use of the new, more methodologically appropriate approach can yield substantively different conclusions.

Results

Examining Effects of Violating the Basic Assumption

We computed results for 648 conditions. Because of space constraints, only representative results for a group of conditions (when $\rho_{TP_a} = .60$, $\rho_{ST_a} = .80$, $\rho_{XX_a} = .70$, and $\rho_{YY_a} = .50$) are presented in Table 1. Full results of this analysis can be found in Le (2003).[9] Below we discuss the results provided by the new procedure and the procedure based on direct range restriction under two conditions: when the model assumption was met and when it was violated.

When the Model Assumption Was Met ($k\varepsilon = 0$)

When $k\varepsilon = 0$, the new procedure accurately estimated the true score correlation ρ_{TP_a}. Under the same condition, the direct range restriction procedure underestimated ρ_{TP_a}, with the underestimation ranging from being negligible (0.03%; when $\rho_{TP_a} = .20$, $\rho_{ST_a} = .10$, $\rho_{XX_a} = .90$, $\rho_{YY_a} = .80$, and $u_S = 0.844$; not shown) to fairly serious (22.67%; $\rho_{TP_a} = .60$, $\rho_{ST_a} = .80$, $\rho_{XX_a} = .70$, $\rho_{YY_a} = .50$, and $u_S = 0.411$; see Table 1). The extent of underestimation mainly depends on (a) the degree of range restriction on S (u_S) and (b) the magnitude of the correlation between S and T (ρ_{ST_a}). The greater the range restriction on S or the higher the correlation between S and T, the more serious the underestimation becomes.

When the Model Assumption Was Violated ($k\varepsilon > 0$)

Both correction procedures underestimated the true score correlation ρ_{TP_a} when the model assumption was violated. The more severely the assumption is violated, the more serious the underestimation becomes. As in the case in which the assumption is met, the degree of underestimation depends largely on the values of u_S and ρ_{ST_a}. Most important, the underestimation resulting from using the new procedure is always less serious than that obtained from the direct range restriction correction. As shown in Table 1, the most serious underestimation obtained from the new procedure occurred when $k\varepsilon = .50$ ($\rho_{ST_a} = .80$ and $u_S = .411$) and is 44.50% ($\hat{\rho}_{TP_a} = .33$ when $\rho_{ST_a} = .60$). Under the same condition, the direct range restriction procedure underestimates ρ_{ST_a} by 63.83% ($\hat{\rho}_{TP_a} = .22$ when $\rho_{ST_a} = .60$).

Results of the current analyses confirm earlier research findings (Hunter et al., 2006; Linn et al., 1981); that is, the conventional direct range restriction correction procedure underestimates true correlation when range restriction is indirect. As expected, the new procedure provides accurate estimates when its key assumption is met. More important, it generally provides less biased estimates for the true score correlation ρ_{ST_a} even when the assumption is violated. Thus, it can be reasonably concluded that the new method should be used, both in individual studies and in meta-analyses, instead of the existing method of direct range restriction when range restriction is indirect.

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[9] Results for the other conditions are qualitatively similar to those presented in Table 1 and would provide the same conclusions about the relative accuracies of Hunter et al.'s (2006) procedure and conventional procedures although the magnitudes of the biases vary.

Table 1
Effects of Violation of the Model Assumption (ρ_{TP_a} = .60, ρ_{ST_a} = .80, ρ_{XX_a} = .70, and ρ_{YY_a} = .50)

Simulated conditions[a]			Unobserved variables[b]				Observed variables[c]				New method results[d]		Direct range restriction correction[e]	
u_S	$k\varepsilon$	ρ_{SP_a}	u_T	u_P	u_Y	ρ_{TP_i}	u_X	ρ_{XX_i}	ρ_{YY_i}	ρ_{XY_i}	ρ_{TP_a}	$B_1\%$	ρ_{TP_a}	$B_2\%$
0.844	0.00	.480	0.903	0.966	0.983	.561	0.933	.656	.483	.316	.600	0.00	.567	−5.50
0.844	0.10	.528	0.903	0.959	0.980	.552	0.933	.656	.479	.310	.591	−1.50	.557	−7.17
0.844	0.20	.576	0.903	0.951	0.976	.544	0.933	.656	.475	.304	.583	−2.83	.546	−9.00
0.844	0.30	.624	0.903	0.942	0.972	.536	0.933	.656	.470	.298	.575	−4.17	.536	−10.67
0.844	0.40	.672	0.903	0.933	0.967	.529	0.933	.656	.465	.292	.568	−5.33	.525	−12.50
0.844	0.50	.720	0.903	0.922	0.962	.521	0.933	.656	.460	.286	.560	−6.67	.515	−14.17
0.603	0.00	.480	0.770	0.924	0.963	.500	0.846	.580	.460	.258	.600	0.00	.510	−15.00
0.603	0.10	.528	0.770	0.907	0.955	.474	0.846	.580	.451	.243	.573	−4.50	.480	−20.00
0.603	0.20	.576	0.770	0.888	0.946	.449	0.846	.580	.441	.227	.546	−9.00	.449	−25.17
0.603	0.30	.624	0.770	0.867	0.936	.423	0.846	.580	.429	.211	.518	−13.67	.418	−30.33
0.603	0.40	.672	0.770	0.844	0.925	.397	0.846	.580	.416	.195	.490	−18.33	.387	−35.50
0.603	0.50	.720	0.770	0.819	0.914	.370	0.846	.580	.401	.179	.460	−23.33	.355	−40.83
0.411	0.00	.480	0.684	0.899	0.951	.457	0.792	.522	.447	.221	.600	0.00	.464	−22.67
0.411	0.10	.528	0.684	0.877	0.940	.415	0.792	.522	.434	.198	.555	7.50	.417	−30.50
0.411	0.20	.576	0.684	0.851	0.929	.373	0.792	.522	.420	.175	.506	−15.67	.369	−38.50
0.411	0.30	.624	0.684	0.822	0.916	.329	0.792	.522	.403	.151	.454	−24.33	.320	−46.67
0.411	0.40	.672	0.684	0.790	0.901	.283	0.792	.522	.385	.127	.396	−34.00	.270	−55.00
0.411	0.50	.720	0.684	0.754	0.886	.235	0.792	.522	.363	.102	.333	−44.50	.217	−63.83

[a] Values of the basic parameters in the Hunter et al. (2006) model. [b] Variables in the model that usually cannot be observed. [c] Variables in the model that are often available in primary studies and were used to make correction for the effects of range restriction and measurement error in the current study. [d] Results (estimate of the true correlation and its bias) provided by the new Hunter et al. (2006) correction procedure. [e] Results provided by the direct range restriction procedure.

Examining the Accuracy of the New Method

Estimating the Mean of the True Score Correlation Distribution

We now turn to the simulation results for the meta-analysis methods. Results are presented in Table 2. The means of true score correlations ($\bar{\rho}_{TP_a}$) were estimated fairly accurately by both new approaches (interactive and Taylor series) under the new meta-analysis method across Conditions 1–3. In general, the Taylor series approach overestimated the real mean true score correlations, and the interactive approach provided more balanced, comparatively accurate estimates. The overestimations, however, are negligible (maximum overestimate is .034 when the mean true score correlation is .500, or 6.8% overestimation, for Distribution 9 under Case 3, Condition 2).

Compared with the new method, the conventional meta-analysis method based on direct range restriction performed poorly (see Condition 4.) The mean true score correlation $\bar{\rho}_{TP_a}$ was consistently underestimated, with underestimation ranging from 36.3% ($\hat{\bar{\rho}}_{TP_a}$ = .446 when $\bar{\rho}_{TP_a}$ = .700; Case 1) to 44.7% ($\hat{\bar{\rho}}_{TP_a}$ = .166 when $\bar{\rho}_{TP_a}$ = .300; Case 2). This degree of underestimation is likely to be consequential, potentially influencing substantive research conclusions. The information available in Condition 4 was the same as that in Condition 1, so the most appropriate comparison is that between these two conditions. However, conclusions are the same when Condition 4 is compared with Conditions 2 and 3.

Estimating the Standard Deviation of the True Score Correlation Distribution

Table 3 shows the results. Under the condition of fixed effects (i.e., SD_ρ = .00), all the approaches overestimated the standard deviation SD_ρ. This result is expected because when the true standard deviation is zero, the estimated standard deviation will be negative 50% of the time because of sampling error, but all the approaches set the estimated variance (and consequently the standard deviation) to zero in such situations. Thus, when averaged across simulations, the results become positively biased (cf. Overton, 1998). Accordingly, the accuracy of the approaches under this condition can be examined only by the magnitudes of their estimated standard deviations ($\hat{SD}_\rho$). As shown in Table 3, on average, the two new approaches overestimated true score standard deviation SD_ρ by .048 to .086 (Var_ρ = .002–.008).

For a concrete idea of the extent of the overestimation, it is helpful to compare the current results with those in the Law et al. (1994) study, which examined the performance of

Table 2
Simulation Results: Estimates of the Mean True Score Correlation ($\bar{\rho}_{TP_a}$)

Information condition	Interactive approach $\hat{\bar{\rho}}_{TP_a}$	Interactive approach B	Interactive approach $\%B$	Taylor series approach $\hat{\bar{\rho}}_{TP_a}$	Taylor series approach B	Taylor series approach $\%B$
Case 1						
Distribution 1 ($\bar{\rho}_{TP_a}$ = .300, $SD_{\rho_{TP}}$ = .000)						
1	.301	0.001	0.33	.304	0.004	1.33
2	.310	0.010	3.33	.317	0.017	5.67
3	.301	0.001	0.33	.309	0.009	3.00
4	.169	−0.132	−43.67			
Distribution 2 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .000)						
1	.499	−0.001	−0.20	.506	0.006	1.20
2	.503	0.003	0.60	.520	0.020	4.00
3	.495	−0.005	−1.00	.509	0.009	1.80
4	.289	−0.211	−42.20			
Distribution 3 ($\bar{\rho}_{TP_a}$ = .700, $SD_{\rho_{TP}}$ = .000)						
1	.682	−0.018	−2.57	.698	−0.002	−0.29
2	.680	−0.020	−2.86	.715	0.015	2.14
3	.710	0.010	1.43	.716	0.016	2.29
4	.446	−0.255	−36.29			
Average						
1		−0.006	−0.81		0.003	0.75
2		−0.002	0.36		0.017	3.94
3		0.002	0.25		0.011	2.36
4		−0.199	−40.72			
Case 2						
Distribution 4 ($\bar{\rho}_{TP_a}$ = .300, $SD_{\rho_{TP}}$ = .055)						
1	.304	0.004	1.33	.309	0.009	3.00
2	.311	0.011	3.67	.319	0.019	6.33
3	.301	0.001	0.33	.307	0.007	2.33
4	.166	−0.134	−44.67			
Distribution 5 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .055)						
1	.494	−0.006	−1.20	.504	0.004	0.80
2	.500	0.000	0.00	.519	0.019	3.80
3	.491	−0.009	−1.80	.504	0.004	0.80
4	.290	−0.211	−42.00			
Distribution 6 ($\bar{\rho}_{TP_a}$ = .700, $SD_{\rho_{TP}}$ = .055)						
1	.684	−0.016	−2.29	.701	0.001	0.14
2	.677	−0.023	−3.29	.711	0.011	1.57
3	.673	−0.027	−3.86	.696	−0.004	−0.57
4	.441	−0.259	−37.00			
Average						
1		−0.006	−0.72		0.004	1.31
2		−0.004	0.13		0.016	3.90
3		−0.012	−1.77		0.002	0.85
4		−0.201	−41.22			
Case 3						
Distribution 7 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .110)						
1	.502	0.002	0.40	.515	0.015	3.00
2	.503	0.003	0.60	.528	0.028	5.60
3	.496	−0.004	−0.80	.512	0.012	2.40
4	.296	−0.204	−40.80			
Distribution 8 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .148)						
1	.499	−0.001	−0.20	.516	0.016	3.20
2	.499	−0.001	−0.20	.529	0.029	5.80
3	.492	−0.008	−1.60	.514	0.014	2.80
4	.295	−0.205	−41.00			

Table 2 (*continued*)

Information condition	Interactive approach $\hat{\bar{\rho}}_{TP_a}$	B	$\%B$	Taylor series approach $\hat{\bar{\rho}}_{TP_a}$	B	$\%B$
Distribution 9 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .184)						
1	.496	−0.004	−0.80	.521	0.021	4.20
2	.496	−0.005	−0.80	.534	0.034	6.80
3	.490	−0.010	−2.00	.512	0.012	2.40
4	.299	−0.202	−40.20			
Average						
1		−0.001	−0.20		0.017	3.47
2		−0.001	−0.13		0.030	6.07
3		−0.007	−1.47		0.012	2.53
4		−0.204	−40.67			

Note. B = difference between the estimated value and true value. $\%B$ = percent difference between estimated value and true value ($\%B$ = 100 × (estimate − true value)/true value). Information Condition 4 = application of the direct range restriction correction; application is based on same information availability as Information Condition 1. Results appear only under the interactive column because there is no Taylor series based procedure for the direct range restriction correction.

the conventional meta-analysis methods based on direct range restriction when their assumption of direct range restriction is met. In that study, the conventional methods overestimated the variance of true score correlation from .003 to .010 (mean SD_ρ = .057–.100) when it was actually zero (Law et al., 1994, Table 4, p. 983). Thus, it appears that the new approaches provide relatively accurate results.

When the true score correlation varies slightly (SD_ρ = .055, Case 2), both new approaches overestimated the true score standard deviation. This pattern of overestimation is also expected because of the same problem discussed earlier. That is, the approaches automatically set the estimated variances to be zero when the calculated values are negative because of sampling error. Although the percentage overestimation appears to be very high under certain conditions, the absolute magnitudes are not (e.g., in Condition 3, the most adverse condition in terms of information availability, average overestimates were .044 and .027 for the interactive approach and the Taylor series approach, respectively).

Results of the current analyses can again be compared with those in Law et al. (1994) to provide more concrete evaluations of the performance of the new meta-analysis approaches vis-à-vis those of the existing meta-analysis methods when their respective assumptions are met. In the Law et al. (1994) study, the interactive method, the best overall method, overestimated the true variance Var_ρ by .002 (Law et al., 1994, Table 6, p. 984), which is equivalent to the overestimation of .015 in SD_ρ. These results should be compared with those provided by the new approaches in Condition 1 as explained earlier (i.e., Condition 1 in the current study is similar to the condition assumed in Law et al., 1994). As can be seen in Table 3, the average overestimations of the interactive and the Taylor series approaches are .023 and .003, respectively. Thus, it is evident that the new approaches compare favorably with the most highly recommended meta-analysis method based on direct range restriction correction (when their respective assumptions of range restriction are met).

The above comparison ignores the fact that range restriction is almost always indirect in practice. As can be seen in Condition 4 in Table 3, under indirect range restriction, the currently best meta-analysis method based on direct range restriction correction (Law et al., 1994) appears to seriously overestimate the standard deviation SD_ρ: The overestimations averaged .070 across simulation conditions in Case 2 (see Table 3). Coupled with the underestimation of mean true score correlation $\bar{\rho}_{TP_a}$ discussed earlier (see Table 2), this finding shows that conventional meta-analysis methods based on direct range restriction produce serious underestimations of the generalizability of relationships between variables of interest.

When true score correlations are more variable (Case 3), both new approaches generally underestimated the standard deviations of true score correlation SD_ρ. The underestimations, however, are generally small in absolute value. The method based on direct range restriction (Condition 4) provides inconsistent estimates of SD_ρ across simulation conditions, ranging from overestimation (.033 when true SD_ρ = .110) to underestimation (−.012 when true SD_ρ = .184).

Reanalysis of McDaniel et al.'s (1994) Meta-Analysis

Data from McDaniel et al. (1994) were reanalyzed with both the interactive and Taylor series approaches. As in the original analysis, we used the sample-based range restriction on interview ratings ($\hat{u}_X$) and restricted independent variable reliability $\hat{\rho}_{XX_i}$. The Pearlman et al. (1980) generalized artifact distribution, however, was specified to be *restricted* dependent variable reliabilities ($\hat{\rho}_{YY_i}$) in the current analysis.

Table 3
Simulation Results: Estimates of the Standard Deviation of the True Score Correlation ($SD_{\rho_{TP}}$)

Information condition	Interactive approach			Taylor series approach		
	$\hat{SD}_{\rho_{TP}}$	B	$\%B$	$\hat{SD}_{\rho_{TP}}$	B	$\%B$
Case 1						
Distribution 1 ($\bar{\rho}_{TP_a}$ = .300, $SD_{\rho_{TP}}$ = .000)						
1	.057	.057		.057	.057	
2	.056	.056		.057	.057	
3	.066	.066		.068	.068	
4	.067	.067				
Distribution 2 ($\bar{\rho}_{TP_a}$ = .500; $SD_{\rho_{TP}}$ = .000)						
1	.061	.061		.048	.048	
2	.066	.066		.047	.047	
3	.081	.081		.069	.069	
4	.121	.121				
Distribution 3 ($\bar{\rho}_{TP_a}$ = .700, $SD_{\rho_{TP}}$ = .000)						
1	.085	.085		.041	.041	
2	.071	.071		.041	.041	
3	.112	.112		.071	.071	
4	.173	.173				
Average						
1		.068			.049	
2		.064			.048	
3		.086			.069	
4		.120				
Case 2						
Distribution 4 ($\bar{\rho}_{TP_a}$ = .300, $SD_{\rho_{TP}}$ = .055)						
1	.070	.015	27.27	.071	.016	29.09
2	.071	.016	29.09	.071	.016	29.09
3	.079	.024	43.64	.081	.026	47.27
4	.073	.018	32.73			
Distribution 5 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .055)						
1	.076	.021	38.18	.062	.007	12.73
2	.074	.019	34.55	.062	.007	12.73
3	.099	.044	80.00	.088	.033	60.00
4	.126	.071	129.09			
Distribution 6 ($\bar{\rho}_{TP_a}$ = .700, $SD_{\rho_{TP}}$ = .055)						
1	.087	.032	58.18	.041	−.014	−25.45
2	.081	.026	47.27	.043	−.012	−21.82
3	.118	.063	114.55	.077	.022	40.00
4	.177	.122	221.82			
Average						
1		.023	41.21		.003	5.45
2		.020	36.97		.004	6.67
3		.044	79.39		.027	49.09
4		.070	127.88			
Case 3						
Distribution 7 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .110)						
1	.095	−.015	−13.64	.078	−.032	−29.09
2	.092	−.018	−16.36	.071	−.039	−35.45
3	.114	.004	3.64	.100	−.010	−9.09
4	.143	.033	30.00			
Distribution 8 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .148)						
1	.120	−.028	−18.92	.101	−.047	−31.76
2	.121	−.027	−18.24	.101	−.047	−31.76
3	.146	−.002	−1.35	.130	−.018	−12.16
4	.158	.010	6.76			

Table 3 (*continued*)

Information condition	Interactive approach $\hat{SD}_{\rho_{TP}}$	Interactive approach B	Interactive approach $\%B$	Taylor series approach $\hat{SD}_{\rho_{TP}}$	Taylor series approach B	Taylor series approach $\%B$
Distribution 9 ($\bar{\rho}_{TP_a}$ = .500, $SD_{\rho_{TP}}$ = .184)						
1	.154	−.030	−16.30	.135	−.049	−26.63
2	.150	−.034	−18.48	.127	−.057	−30.98
3	.174	−.010	−5.43	.156	−.028	−15.22
4	.172	−.012	−6.52			
Average						
1		−.024	−16.29		−.043	−29.16
2		−.026	−17.70		−.048	−32.73
3		−.003	−1.05		−.019	−12.16
4		.010	10.08			

Note. B = difference between the estimated value and true value. $\%B$ = percent difference between estimated value and true value ($\%B$ = 100 × (estimate − true value)/true value). Information Condition 4 = application of the direct range restriction correction; application is based on same information availability as Information Condition 1. Results appear only under the interactive column because there is no Taylor series based procedure for the direct range restriction correction.

McDaniel et al. (1994) reported the operational validities of employment interviews (i.e., correlation between interviews with job performance, not corrected for measurement error in interview ratings). The new approaches discussed thus far have been presented for true score correlations; so the results (the true score correlation between interviews and job performance constructs and its SD_ρ) must be attenuated here to account for the effect of measurement error in interview ratings. This process requires information on the unrestricted independent variable reliability (ρ_{XX_a}), which can be estimated by solving Equation 3 for ρ_{XX_a}:

$$\hat{\rho}_{XX_a} = 1 - \hat{u}_X^2(1 - \hat{\rho}_{XX_i}). \tag{22}$$

The interactive and Taylor series approaches yielded comparable results; so we report only results from the interactive approach. Table 4 presents the results. As shown in the table, the estimate of overall validity of employment interviews is .393, indicating that the value reported by McDaniel et al. (1994; .370) underestimated the true validity by 5.85%. Validities of job-related structured and unstructured interviews were estimated to be .440 and .407, respectively. From these results, it appears that the validity of unstructured interviews is not much lower than that of structured interviews, contrary to McDaniel et al.'s results. As for estimation of standard deviations, results in Table 4 show that McDaniel et al. overestimated the standard deviations of validities of employment interviews, with the overestimation ranging from 10.1% (for all interviews) to 27.5% (for unstructured interviews). Combined with the underestimation of the mean validities mentioned above, these overestimations result in rather serious underestimations of the 90% credibility values (ranging from 35.5% to 44.0%). This is important because the 90% credibility value is typically used to determine generalizability of the relationship.

In conclusion, the findings show that McDaniel et al.'s (1994) meta-analysis generally underestimated the validities of employment interviews. The underestimations of the mean validities, however, are moderate because of the com-

Table 4
Reanalysis of McDaniel et al.'s (1994) Meta-Analysis: Results and Comparisons

Interview distributions	N	k	Bare bones analysis $\bar{r}$	Bare bones analysis Var(e)	Bare bones analysis Var(r)	Reanalysis results Validity $\hat{\rho}_{XP_a}$	Reanalysis results SD_{validity} $\hat{SD}_{\rho XP_a}$	Reanalysis results 90% CV	McDaniel et al. (1994) original results Validity $\hat{\rho}_{XP_a}$	McDaniel et al. (1994) original results SD_{validity} $\hat{SD}_{\rho XP_a}$	McDaniel et al. (1994) original results 90% CV	% difference between the approaches Validity	% difference between the approaches SD	% difference between the approaches CV
All interviews	25,244	160	.200	.0060	.0239	.393	.209	.124	.370	.230	.080	−5.85	10.05	−35.48
Job-related structured	11,801	89	.237	.0069	.0337	.440	.245	.125	.440	.280	.070	0.00	14.29	−44.00
Job-related unstructured	8,985	34	.177	.0036	.0119	.407	.102	.277	.330	.130	.170	−18.92	27.45	−38.63

Note. N = total sample size; k = number of studies; $\bar{r}$ = mean observed validity; Var(e) = variance due to sampling error; Var(r) = variance of observed correlations; 90% CV = credibility value for the distribution of true validities; % difference = 100 × (original value − reanalysis value)/reanalysis value; CV = credibility value.

bined neutralizing effects of two methodological problems discussed earlier: (a) the underestimating effect created by the use of meta-analysis methods based on direct range restriction correction and (b) the overestimating effect resulting from using independent variable reliabilities estimated in the restricted population as if they came from the unrestricted population.

Discussion

The current study corroborates Hunter et al.'s (2006) analytically based conclusions about the problem caused by using meta-analysis methods based on the direct range restriction model when range restriction is actually indirect. As shown in the Monte Carlo simulation, under the condition of indirect range restriction, the interactive meta-analysis method based on direct range restriction consistently underestimated the true score correlations across different configurations of simulated parameters. The underestimation ranges from 36% (Case 1, when $\rho_{TP_a} = .50$) to 45% (Case 2, when $\rho_{TP_a} = .30$). Because range restriction is likely to be indirect in most research situations, it is indeed sobering to note that the best interactive meta-analysis method to date could provide such biased estimates—estimates that can potentially affect many substantive research conclusions.

The reanalysis of McDaniel et al.'s (1994) meta-analysis provides a real-world examination of the problem resulting from the combined effects of two methodological issues that affect most meta-analyses in the literature. Although the underestimation may not be quite as serious as suggested by the Monte Carlo simulations (partially because of the abovementioned offsetting effects and rather high reliabilities of interview ratings reported in the primary studies), the use of inappropriate meta-analysis methods may have led to erroneous conclusions about the relative magnitudes of the validities of structured and unstructured interviews (i.e., in the original analysis, the percentage difference in the validities of the interviews is 25%, whereas it is only 7.5% in the reanalysis).

These findings suggest that many previous meta-analyses in the literature based on existing methods underestimate the true relationships between constructs. Even in cases in which the underestimations are moderate (as in the case of McDaniel et al.'s, 1994, study examined here), they may still be problematic when such meta-analytically estimated correlations are further used to examine competing models of structural–causal relationships among constructs by means of path analysis or structural equation modeling (cf. Becker, 1989; Becker & Schram, 1994; Tett & Meyer, 1993; Viswesvaran & Ones, 1995). Further, combined with the fact that existing meta-analysis methods based on the direct range restriction correction generally overestimate the standard deviation of the true score correlation (SD_ρ), the underestimation of the mean would be likely to result in erroneous conclusions about the generalizability of the relationships between constructs.

Results of this study demonstrate that the problem caused by the use of the inappropriate meta-analysis methods is indeed serious enough to distort many research conclusions. Hunter et al. (2006) suggested the new meta-analysis method as a solution for the problem. The new meta-analysis method is based on the crucial assumption that the effect of selection on the third variable S on the dependent variable P is fully mediated by the independent variable T. The accuracy of the new method depends on the extent to which the assumption holds in practice. On theoretical grounds, it is expected that the assumption indeed holds in many research situations. However, even when the assumption is violated, the new method was found to provide less biased estimates than those provided by the existing method based on direct range restriction. Thus, results from the present study demonstrate the overall superiority of the new meta-analysis method when range restriction is indirect, the common case in practice.

Correction for indirect range restriction in meta-analysis is a complicated process because of the nonlinearity of the attenuating effect (Mendoza & Reinhardt, 1991). This nonlinear effect is more serious under the condition of indirect range restriction as compared with direct range restriction, because the degree of range restriction in true score T is more severe than that on observed score X. Both approaches introduced for the new meta-analysis method (interactive and Taylor series) are therefore approximation processes (as are many statistical estimation procedures). And apart from the theoretical (substantive) assumption of the new meta-analysis method discussed above, those approximation methods for meta-analysis require a methodological assumption: the independence among the essential components in Equation 1. As explained earlier, this assumption is in fact always violated to a certain degree.

Given all these complexities, it is encouraging that the two new meta-analysis approaches perform reasonably well. Across all the conditions of simulations and information availability, both the Taylor series and the interactive approaches yielded very accurate estimates of the mean true score correlations. Estimating the standard deviation of true score correlation SD_ρ proved to be more challenging, as expected from previous research findings (e.g., Mendoza & Reinhardt, 1991). The new approaches appear to provide biased estimates of the standard deviations. Nevertheless, as discussed earlier, the magnitudes of biases are moderate and unlikely to lead to serious problems in substantive research. Perhaps more important, results of the Monte Carlo simulation analyses demonstrate that overall the new approaches can provide more accurate estimates of the means and standard deviations of the true score correlations than can conventional procedures based on direct range restriction and therefore should be used by empirical researchers in place of the conventional meta-analysis methods.[10] A computer program (Schmidt & Le, 2004) based on the Hunter et al. (2006) method has been developed and is available to facilitate use of the new procedure in meta-analyses to correct for the biasing effects of indirect range restriction.[11]

Although it is disappointing to find that existing meta-analysis methods and published meta-analyses based on them may seriously underestimate relations between constructs, the findings of this study open opportunities to reexamine many important research conclusions that have been reached on the basis of the less-than-optimal analytical methods. Many published meta-analyses, especially those in the fields of educational and employment selection, may have seriously underestimated relationships between constructs.[12] Conceivably, reanalyses of those studies may yield results that can challenge established knowledge in these areas and many others.

[10] A reviewer questioned the generalizability of the conclusion about the accuracy of the two approaches under the new Hunter et al. (2006) meta-analysis method to other conditions not presented here. This question can partially be answered by Le (2003), who also examined two additional distributions of the true score correlations (a bimodal distribution [$\bar{\rho}_{TP_a} = .150$, $SD_\rho = .163$] and a rectangular distribution [$\bar{\rho}_{TP_a} = .225$, $SD_\rho = .144$]) and three other distributions of range restrictions u_X. Results obtained from these conditions are very similar to those presented here. That is, both approaches (interactive and Taylor series) yielded very accurate estimates of the mean true score correlations ($\hat{\bar{\rho}}_{TP_a}$) and reasonably accurate estimates of the standard deviations ($S\hat{D}_\rho$).

[11] Readers can refer to Hunter and Schmidt (2004) for information about how to obtain the program.

[12] Of course, there are published meta-analyses that make no attempt to correct for either range restriction or measurement error (e.g. Mullen & Copper, 1994; Spangler, 1992). The underestimation produced in those meta-analyses is much greater than that in meta-analyses that corrected for direct range restriction when the correction should have been for indirect range restriction.

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Appendix A

Constructing the Distribution of Range Restriction in the Independent Variable True Score (u_T)

When there is indirect range restriction, independent variable reliability in the unrestricted population (ρ_{XX_a}) and range restriction on independent variable observed scores (u_X) are not independent of each other because the latter is a function of the former and range restriction of the independent variable true scores (u_T). This dependency makes it impossible to derive the u_T distribution by simply combining the u_X and ρ_{XX_a} distributions as per Equation 17. Because of that, an iterative approach is needed to estimate the distribution of u_T. The approach involves initially selecting a plausible distribution for u_T ($\hat{u}_T$). The distribution includes a number of representative values of $\hat{u}_T$ together with their respective frequencies. All those values of $\hat{u}_T$ are then entered into Equation 8 with each value of ρ_{XX_a} in its distribution to estimate $\hat{u}_X$. The resulting values of $\hat{u}_X$ form a distribution with the frequency of each value being the product of the corresponding frequencies of $\hat{u}_T$ and ρ_{XX_a} in their respective distributions (this calculation is possible because $\hat{u}_T$ and ρ_{XX_a} are independent of each other). This $\hat{u}_X$ distribution is then compared with the observed distribution u_X, on the basis of a preset criterion. If they are different, as determined by the criterion, a new iteration is started. A new plausible distribution of $\hat{u}_T$ will be constructed by keeping the original values of $\hat{u}_T$ but systematically changing their frequencies. The whole process described above is repeated until the distribution of $\hat{u}_X$ is similar to the observed u_X distribution (as determined by the criterion). Further details can be found in Le (2003). A computer program was written in SAS to facilitate the process (which may require hundreds of thousands of iterations). The program is available from Huy Le upon request.

Appendix B

Analytic Steps for the New Meta-Analysis Interactive Approach

As mentioned in the text, the first step involved estimating the hypothetical distribution of observed correlations that would obtain when (a) all the artifacts are fixed at their mean values and (b) there is no sampling error. The mean of this hypothetical distribution is the sample size weighted mean of the observed correlations:

$$\hat{\bar{\rho}}_{XY_i} = \frac{\sum_j N_j \hat{\rho}_j}{\sum_j N_j},$$

where N_j and $\hat{\rho}_j$ are the sample size and observed correlation of a primary study j included in the meta-analysis, respectively.

The variance of the hypothetical distribution is estimated by subtracting from the observed variance (a) sampling error variance and (b) variance due to the combined effects of variation across studies in the three statistical artifacts (measurement error in the dependent variable and independent variable measures and range restriction in the independent variable):

$$\mathrm{Var_{hyp}} = \mathrm{Var_{obs}} - \mathrm{Var_e} - \mathrm{Var}_{\rho_{XX}\rho_{YY}u_T},$$

where $\mathrm{Var_{hyp}}$ = the hypothetical variance of interest, $\mathrm{Var_{obs}}$ = observed variance ($\mathrm{Var_{obs}} = \frac{\sum_j N_j(\rho_j - \hat{\bar{\rho}}_{XY_i})^2}{\sum_j N_j}$), $\mathrm{Var_e}$ = averaged sampling variance of the primary studies ($\mathrm{Var}_e = \frac{\sum_j N_j\left(\frac{(1-\hat{\bar{\rho}}^2_{XY_i})^2}{N_j - 1}\right)}{\sum_j N_j}$), and $\mathrm{Var}_{\rho_{XX}\rho_{YY}u_T}$ = variance due to the combined effect of the three statistical artifacts.

$\mathrm{Var}_{\rho_{XX}\rho_{YY}u_T}$ is calculated by the following steps:

1. Disattenuate the mean of the hypothetical distribution ($\hat{\bar{\rho}}_{XY_i}$) using the means of the artifact distributions.
2. Create a 3-D matrix with the cells being all the possible combinations of values of reliability of dependent variable measure (ρ_{YY_i}), reliability of independent variable measure (ρ_{XX_a}), and range restriction on the independent variable (u_T).
3. For each cell, calculate the expected value of the observed correlation by attenuating the disattenuated mean value obtained in Step 1 using the values of the artifacts in the cell.

(*Appendixes continue*)

4. Compute the variance of the correlations obtained in Step 3 across cells, weighting each by its cell frequency. Because the statistical artifacts (ρ_{XX_a}, ρ_{YY_i}, and u_T) are assumed to be independent, cell frequencies are computed by taking the products of the frequencies of the artifacts in their respective distributions. For example, frequency for a cell defined by the values of $\rho_{XX_a} = .90$ (frequency = .15; see Figure 2), $\rho_{YY_i} = .80$ (frequency = .06; see Figure 2), and $u_T = .499$ (frequency = .14; see Figure 3) is .00126 (.15 × .06 × .14 = .00126). The resulting variance is $\mathrm{Var}_{\rho_{XX}\rho_{YY}u_T}$.

The hypothetical distribution obtained here is assumed to be univariate normally distributed. Sixty-one values in this distribution (from −3.00 SD_{res} to 3.00 SD_{res}, by steps of 0.10 SD_{res}) are then disattenuated by using the procedure described in Step 1. These resulting disattentuated values form the distribution of the true correlation ρ_{TP_a}. The mean true correlation ($\bar{\rho}_{TP_a}$) and its variability (SD_ρ) are then estimated directly from that distribution.

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