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Meta-Analysis of Bidirectional Relations in Personality–Job Performance Research

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Standard meta-analysis (Hunter & Schmidt, 1990a) assumes unidirectional (i.e., all positive or all negative) predictor–criterion relations. We challenge this assumption in the context of personality–job performance linkages based on several lines of evidence supporting the coexistence of true positive and true negative correlations involving the same trait. Subjecting such bidirectional relations to standard meta-analysis will underestimate effect sizes to an unknown degree owing to cancellation of positive and negative values. A modification of standard procedures is proposed that accounts for the possibility of bidirectionality. It employs successive iteration of an initial estimate of the absolute correlation, accounting for sample sizes and the sampling distribution of the correlation. Tests of the procedure using hypothetical

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distributions show it works as expected. Application to previously documented personality–job performance relations (Tett, Jackson, & Rothstein, 1991) yields interpretable effect sizes substantially stronger than previously reported estimates. Implications for interpreting prior meta-analytic findings in this area are discussed.

Relations between personality and job performance have been the subject of formal review for over 30 years. In their classic article, Guion and Gottier (1965) concluded that personality had not, up to that time, shown much promise for predicting job performance; however, they gave grounds for optimism by emphasizing the need for greater care in establishing the conceptual bases for personality–performance linkages as a means of promoting validity. In support of Guion and Gottier's call for theory, Tett, Jackson, and Rothstein (1991; Tett, Jackson, Rothstein, & Reddon, 1994) showed using meta-analysis that personality measures predict job performance about twice as well when hypotheses are formed from careful consideration of the trait requirements of the given job. If the true potential of personality is to be realized, it is critical to distinguish cases involving a priori hypotheses from those employing "shotgun" empiricism. Ignoring this distinction in standard meta-analysis can result in serious underestimation of the value of personality because results from confirmatory studies, which are more likely to be favorable, will be washed out by weaker exploratory findings (Tett et al., 1991; Tett, Jackson, et al., 1994).

A related and equally important issue to emerge from Tett et al.'s (1991) meta-analysis (cf. Ones, Mount, Barrick, & Hunter, 1994; Tett, Jackson, et al., 1994) concerns the directionality of personality–performance relations. Review of the literature supports the wisdom of human resource practitioners that many personality scales can and do yield bidirectional relations with job performance. That is, they can show a meaningful relation with a criterion measure in either direction, positive or negative, depending on conceptually relevant factors. Extraversion, for example, may be required in some jobs and introversion in others. (Note that our use of the term *bidirectional* does not denote reverse causality as in nonrecursive structural models.) Our aims in this article are to (a) evaluate the problem of bidirectionality in personality–job performance relations, (b) explicate the critical implications of this problem for meta-analysis, (c) describe modifications to standard meta-analytic procedures (Hunter & Schmidt, 1990a) that address the problem, and (d) present results from a re-analysis of Tett et al.'s (1991) compiled data reflecting new and important methodological refinements.

BIDIRECTIONALITY OF PERSONALITY–JOB PERFORMANCE RELATIONS

It is important at the outset to recognize that the strength and direction of a correlation are conceptually and practically separable. How far a correlation is from zero reveals how important a variable is in explaining and/or predicting another variable. Whether the correlation is positive or negative reveals part of the qualitative nature of the relation. Consider the following example. Two variables, *A* and *B*, have population correlations of .3 and –.6, respectively, with variable *Y*. Regardless of the difference in the strength of their relations with *Y*, it is meaningful that *A* and *B* are related to *Y* in opposite directions. At the same time, regardless of the difference in direction, it is meaningful to compare *A* and *B* with respect to relation strength (i.e., B is more strongly related). The separability of strength and direction is recognized in interpretations of multiple *R*, eta, and, in a similar sense, *F*. It has special implications at the aggregate level. In our example, the average correlation (i.e., –.15) gives the overall directional relation with *Y*. Although allowing an interpretation of strength, this average, in fact, underestimates strength independent of direction. True average strength can be determined by averaging the absolute values of the two correlations (i.e., $|.45|$). Both strength and direction are important and are used routinely in describing targeted relations. As described below, however, meta-analysis can, under certain conditions, call for estimation of relation strength independent of direction.

Standard meta-analysis (Hunter & Schmidt, 1990a) was designed for aggregation of repeated estimates of relations predictable in one direction—that is, either positive or negative. The assumption of unidirectionality is sufficient when dealing with many links in industrial/organizational psychology, including that between cognitive ability and (positively keyed) job performance. In such cases, observed negative correlations may be attributed to sampling error. Not all relations of interest, however, permit such a straightforward interpretation of negative values. Bidirectional relations can pose a problem for standard meta-analysis because averaging positive and negative values, as occurs in standard procedures, will underestimate the overall strength of targeted linkages (i.e., independent of direction) due to simple arithmetic cancellation (e.g., other things being equal, averaging a true –.25 correlation and a true .25 value gives .00). The results of such a meta-analysis cannot be interpreted meaningfully with respect to strength independent of direction. In later sections, we present evidence for bidirectionality in personality–job performance relations and describe several approaches to resolving the problem of bidirectionality in meta-analysis. First, let us consider some conceptual issues guiding expectations of bidirectionality.

Why Should We Expect Bidirectional Relations Between Personality and Job Performance?

Expectations of bidirectionality derive from three general observations. First, in the context of everyday living, the desirability of a given pole of a given trait is rarely if ever universal. For example, most will agree that it is generally good to be planful:

effective planning is critical for success in many endeavors, especially complex ones. It makes people and events easier to predict, which lends stability and security in the face of uncertainty. This does not imply, however, that impulsivity (i.e., low planfulness) is never appreciated or that planfulness never interferes with productivity (e.g., analysis paralysis). Similarly, one may, in general, prefer a companion who is outgoing and energetic, but there will be times when the company of someone more reserved and demure is preferred. We suggest there are few exceptions to such bidirectional desirability of personality traits. Even in the case of hostility, which may most often be undesirable, one can postulate times and places in which this facet of neuroticism is advantageous (e.g., certain competitive situations).

A second and related observation is that jobs are diverse with respect to valued behaviors. In customer service, for example, rewarded behaviors include politeness, following up on customer requests, and being sensitive to individual customers' needs. Such behaviors may be counterproductive in jobs like border patrol officer, security guard, and foot soldier, where humanistic values are generally subordinate to those of national or company security. Important differences are possible even within job families. For instance, one company may value assertive sales tactics, whereas another might encourage a softer, more conservative approach. Similarly, one work group may welcome a new member who is assertive, whereas another group would want someone more submissive. In sum, trait poles conducive to success in one work situation can be opposite from those suited to another.

A third point stems from the fact that personality, more than cognitive ability, is multidimensional. That personality is composed of multiple, distinct factors (three, five, or more, depending on one's favorite level of specificity) does not by itself imply bidirectionality. It does, however, allow greater opportunity for bidirectionality. Given the complexity of personality and jobs, rationales regarding directionality are likely to be trait and job specific.

These considerations lead us to propose that the direction of specific trait–performance relations are moderated by trait-relevant situational demands. There has been no detailed discussion of this issue in the literature. Three general aspects of the work setting that merit consideration are (a) job tasks (i.e., what the worker does), (b) work groups (i.e., the worker's immediate co-workers, including supervisors, peers, and subordinates), and (c) organizational culture (i.e., the company's "personality" made evident chiefly by the words and actions of senior management). Each aspect will vary from job to job in providing opportunities for the expression of different traits. Which pole of a trait is considered desirable will depend on whether the given job task set, work group, or culture facilitates valued behavior (e.g., performance, tenure) for someone at one pole and not the other.

In support of the need to consider situational factors in anticipating the direction of trait–performance linkages, Day and Bedeian (1991) found that Work Orientation, a Conscientiousness facet, interacted with organizational climate (e.g., Warmth–Support) in predicting job performance in accountants. The nature of the interaction suggested a positive trait–performance relation for employees in positive climates and a (weaker) negative relation for those in negative climates. Studies of this type are rare. More research is needed to test the interactionist basis for bidirectionality of trait–performance linkages.

Having sketched out a conceptual platform for bidirectional relations between personality and job performance, let us now consider the evidence. We can identify three distinct sources: (a) probabilistic analysis of negative observed validities from past research, (b) review of significantly negative validities from representative studies, and (c) results from previous meta-analyses in this area. Each is discussed next, in turn.

Probabilistic analysis. Tett, Jackson, et al. (1994) quantified the problem of negative values in relations between personality and job performance using the data of Tett et al. (1991). They showed that the proportion of 645 observed validities that were negative (after controlling for the direction of keying) could not be attributed entirely to sampling error. In fact, the significantly negative correlations outnumbered those expected due to chance by a ratio of 28 to 1, and all negative correlations (regardless of significance) outnumbered sampling error expectations by 2.5 to 1. These results indicate that, through inappropriate cancellation of positive and negative correlations, meta-analyses conducted under the assumption of unidirectionality will underestimate the value of personality measures in predicting job performance.

Review of representative studies. The researchers also described several cases from Tett et al.'s (1991) data set in which relations between Big Five facet measures and job performance were opposite in sign to those obtained from broad meta-analytic aggregations, yet were interpretable in light of sample, criterion, and other contextual factors. Day and Silverman (1989), for example, found a correlation of –.31 ($p < .05$) between a facet of Extraversion (i.e., Ascendancy) and global job performance in accountants, which supported directional expectations based on job analysis. Significant negative values were also reported for several other criteria, including –.38 ($p < .01$) for Potential. Review of statistically significant results from representative studies reported more recently further challenges the unidimensionality assumption with respect to the Big Five. (Performance in all cases is positively keyed.)

In a study of naval electronics trainees, Driskell, Hogan, Salas, and Hoskin (1994) found that Prudence, a facet measure of Conscientiousness from the *Hogan Personality Inventory* (HPI; R. Hogan, 1986), correlated –.15 with a training criterion measure including number of modules completed and work speed. This suggests that conscientious workers, perhaps in being overly concerned with detail, can spend too much time on too few tasks. J. Hogan, R. Hogan, and Murtha (1992) reported –.34 and –.18 relations between overall managerial performance in a trucking company and Planful and Perfect, respectively, both components of HPI-Prudence. Bunce and West (1995) found that Task Orientation and Intrinsic Job Motivation, both aspects of Conscientiousness, correlated –.14 and –.27, respectively, with innovation in health services employees. Along similar lines, J. Hogan and R. Hogan (1993) reported correlations ranging from –.37 to –.42 between HPI-Prudence and measures of peer-rated musical performance. HPI-Prudence also correlated –.17 with artistic interests and –.14 with aesthetic motives. Thus, in jobs requiring expedient completion of numerous tasks and/or creative and artistic tendencies, being conscientious may be a liability. Such findings raise doubts about unidirectional assumptions concerning conscientiousness evident in prior research (e.g., Barrick & Mount, 1991).

Several recent studies suggest that Extraversion, too, can be detrimental to job performance. Hayes, Roehm, and Castellano (1994) reported that machine operators high in Sociability were outperformed by their introverted counterparts on a variety of dimensions judged a priori to be relevant to success in a total quality management program. Specifically, Sociability correlated negatively with Attendance (–.29), Achievement Orientation (–.26), Works Independently (–.26), and Overall and Composite criteria (–.24 and –.23, respectively). In reviewing research on military pilot selection, Turnbull (1992) concluded that the best pilot trainees are introverts. He also noted findings indicating that the safest drivers are introverts (Shaw & Sichel, 1970). In a cross-cultural investigation, Furnham and Stringfield (1993) found that Extraversion correlates –.13 (and Introversion .15) with productivity in Chinese managers. Such findings, all statistically significant, suggest that being outgoing can interfere with performance in some job settings.

Other results further challenge the assumption of unidirectionality regarding personality–job performance relations involving the Big Five. Hayes et al. (1994), in their study on machine operators, observed negative relations between HPI-Intellectance, a measure of Openness to Experience, and Attendance (–.29), Works Independently (–.23), and the Composite performance criterion (–.18). J. Hogan, R. Hogan, and Murtha (1992) obtained a –.27 validity for Experience Seeking in relation to managerial performance. J. Hogan, R. Hogan, and Gregory (1992) reported a –.15 correlation between HPI-Adjustment, a positive indicator of Emotional Stability, and supervisors' nominations of performance in trucking industry sales representatives. Results for specific item clusters included negative relations between various performance dimensions and No Guilt (e.g., –.28 with Revenue), Self-Focus (e.g., –.34 with Revenue), and Intellectual Games (–.18 with Supervisory Ratings). In light of meta-analytic results supporting the validity of integrity tests in the prediction of employee delinquency (Ones, Viswesvaran, & Schmidt, 1993), it is notable that Murphy and Lee (1994) reported negative correlations between diverse integrity measures and positive indicators of Openness to Experience and Extraversion. A personality-based integrity measure, for example, correlated –.28 and –.33 with Intellectance and Sociability, respectively. Taken together, these findings suggest that less delinquency (i.e., higher performance) may be expected from those low on Openness, Extraversion, or both.

Review of prior meta-analytic results. Previous meta-analyses of personality–job performance relations provide corroborating evidence for the existence of true negative validities for the Big Five in predicting job performance. Bidirectionality will manifest most clearly in meta-analysis as (a) an average correlation near zero and (b) substantial variance in correlations left unexplained by statistical artifacts. Barrick and Mount (1991) reported mean correlations ranging from .02 to .15 (median = .05) and corresponding percentages of unexplained variance ranging from 17 to 58 (median = 40) for the Big Five in relations with performance ratings. Similar results were provided for other criteria (e.g., Extraversion correlated .06 on average with personnel data, with 67% unexplained variance). In a more recent study based on data sources completely different from Barrick and Mount's, Salgado (1997) reported mean validities for three of the Big Five dimensions ranging from .06 to .10, with percentages of unexplained variance ranging from 36 to 63 (average correlations for the remaining two dimensions were around zero, but nearly all variance was explained by artifacts). It is interesting to note that Extraversion correlated –.07 with sales performance, on average, with 47% of the variance left unexplained. The direction of this relation is opposite that reported by Barrick and Mount (1991). Along similar lines, Hough (1992) reported mean validities of .09 and –.06 for Intellectance in predicting job proficiency in managers and health care workers, respectively. Corresponding validities of .18 and –.24 were observed for Achievement. Such findings support the existence of bidirectional relations between personality and job performance.

All told, the research cited in the preceding paragraphs suggests that negative relations are possible and, moreover, interpretable in specific settings. Failure to consider the possibility of meaningful negative validities in meta-analysis of relations involving the Big Five will result in underestimation of the overall power of personality measures in the prediction of job performance. As described in the next section, meta-analytic moderator analysis cannot for practical reasons address the bidirectionality problem. Alternative approaches to meta-analysis of bidirectional relations are therefore worth considering. Particular attention is given to an approach that uses absolute values, which extends the method employed by Tett, Jackson, et al. (1994) by allowing refinement of an important assumption guiding associated statistical corrections. Also, the main data of Tett et al. (1991) are reanalyzed using the revised procedure. Resulting estimates of personality–performance relations are more optimistic than any reported to date with respect to the overall predictive strength of personality variables.

SOLUTIONS TO THE PROBLEM OF BIDIRECTIONAL RELATIONS IN META-ANALYSIS

We can identify two ways to conduct meta-analysis of bidirectional relations. The first method, although desirable for its potential to assess the bases for differences between positive and negative relations, is virtually impossible to undertake in the majority of cases. The second method can provide an estimate of the overall strength of personality measures in predicting job performance independent of direction based on all available relevant studies.

First, if it were possible to know the key characteristics of the work environments in which data in individual studies were gathered—characteristics that can affect the direction of a given relation—then it would be possible to conduct moderator analysis using established meta-analytic methods (Hunter & Schmidt, 1990a). In this approach, studies (or samples) would be grouped into discrete categories defining the moderator variable (e.g., jobs requiring extroverts vs. introverts), as determined by theory, job analysis, or both, and then mean relations would be compared between groups. The expectation would be a positive and a negative mean validity. In a slight variation on this approach, studies (or samples) might be coded along a continuum with moderator effects being assessed through correlation with observed relations rather than by way of subgroup comparison.

A potential problem with this approach in the case of personality–job performance relations is that the "key characteristics" that could influence direction are rarely described in sufficient detail in source studies to permit reliable detection of possible moderators, reverse directionality, or both (Tett et al., 1991; Tett, Jackson, et al., 1994). An exception would be confirmatory studies in which the expected direction of the relation is determined from theory, job analysis, or both. In the case of personality–job performance relations, however, confirmatory studies have been in the minority. In fact, unless it is an explicit focus of research, trait-relevant information on organizational culture and other potentially relevant situational factors (e.g., Day & Bedeian, 1991) is hardly ever provided in source studies. Lack of such information precludes use of standard moderator analysis and/or keying of observed validities in the direction of predictability. Accordingly, if the available literature is to provide the basis for estimating the overall importance of personality measures in the prediction of job performance, alternative meta-analytic procedures merit consideration.

The second strategy for assessing bidirectional relations in meta-analysis uses absolute values. This approach does not require knowledge of whether or not the reported correlations between personality and job performance in source studies should have been positive or negative. As noted originally by Tett et al. (1991), the use of absolute values poses problems in meta-analysis. One concern is that the mean validity based on absolute values will overestimate predictive power due to capitalization on randomly negative values resulting from sampling error (e.g., where the population correlation equals 0, the mean absolute value observed correlation will be greater than 0). A further concern, noted by Ones et al. (1994), is that the cross-study variance of absolute values is restricted relative to that of signed values. Use of absolute values in meta-analysis thus requires corrections for (a) upward bias in the mean and (b) restriction in observed variance. Such corrections are made possible by knowledge of the sampling distributions of the signed and absolute value correlations.

THE SAMPLING DISTRIBUTIONS OF SIGNED VERSUS ABSOLUTE VALUE CORRELATIONS

The sampling distribution of the absolute value correlation differs in several ways from that of the signed correlation. Two differences that are critical in meta-analysis are that the mean will be higher and the variance will be smaller for the absolute value correlation. These two effects are depicted in Figure 1, where rho (i.e., the population correlation; ρ) is zero and *N* for each contributing study is 50. Note that the mean of the absolute value correlations (.11) is higher than that of the signed values (0). The difference between these two means is the degree to which

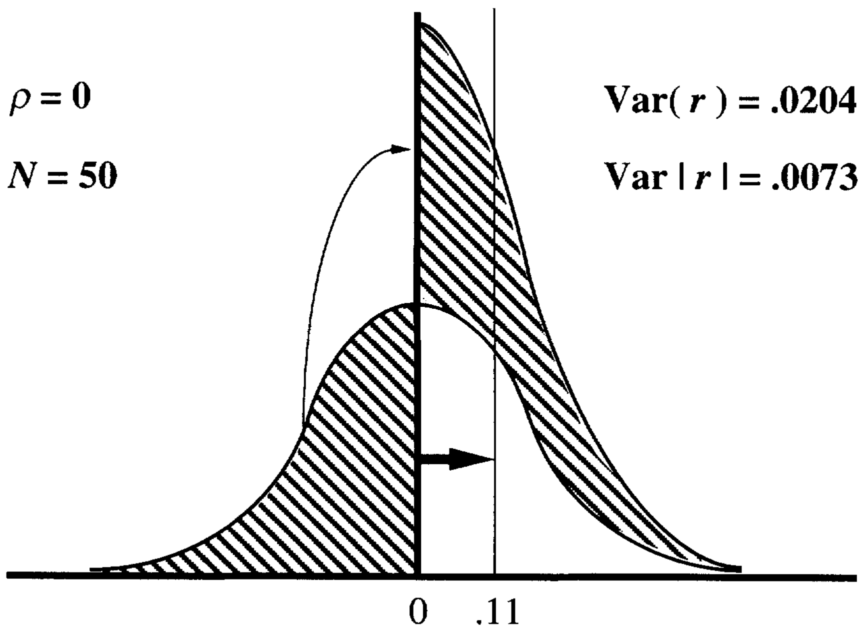

FIGURE 1 Sampling distribution for signed and absolute value correlations where r = 0 and *N* = 50, showing upward bias in the mean and restriction of variance.

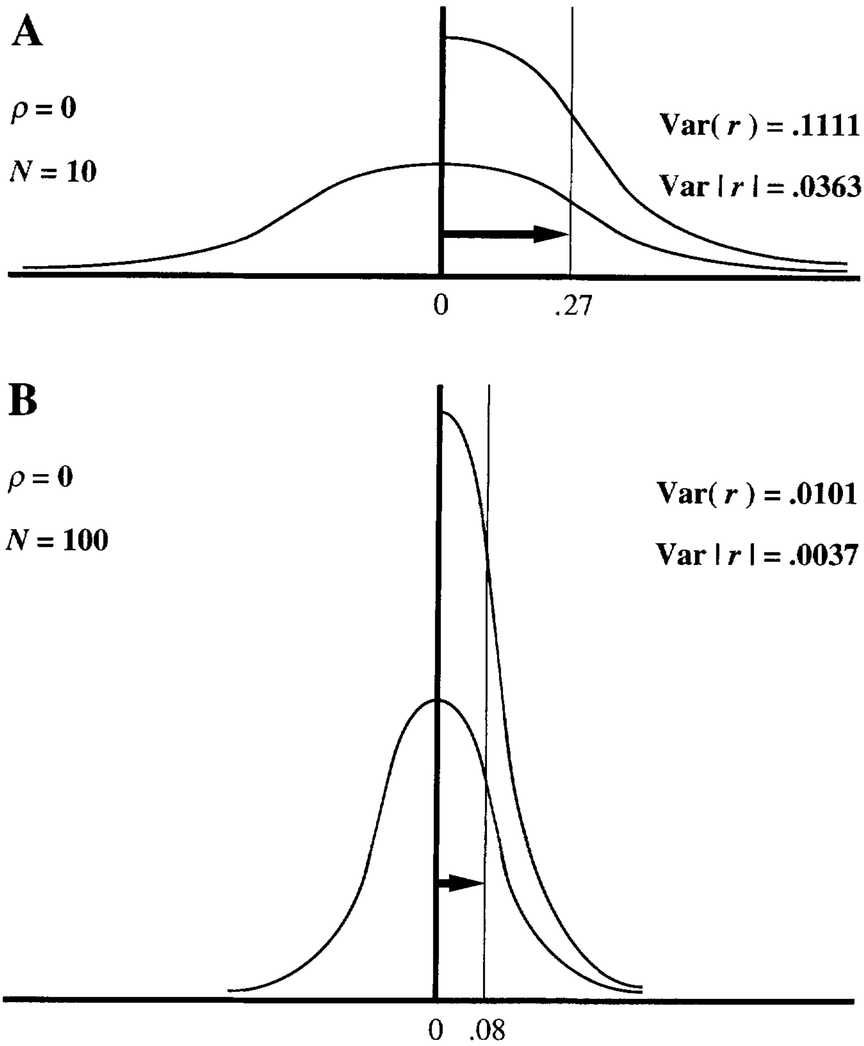

FIGURE 2 Sampling distributions for signed and absolute value correlations, where r = 0 and (A) $N = 10$ and (B) $N = 100$.

use of absolute values inflates the estimate of rho under the specified assumptions regarding *N* and rho. Also note that the variance of the absolute value correlations is smaller than that for the signed correlations. The ratio of the larger (i.e., unrestricted) to the smaller (i.e., restricted) variance may be used to correct the degree to which observed variance is underestimated when absolute values are used.

Corrections for the use of absolute values in meta-analysis are complicated by the fact that the strength of the two noted effects depends on *N* and rho, which vary. Figure 2 shows two sampling distributions for the signed and absolute value correlation where rho = 0. In Part A, *N* is 10, and in Part B, *N* is 100. Comparing Figures 1 and 2 shows that, as *N* increases, both upward bias in the mean and restriction in

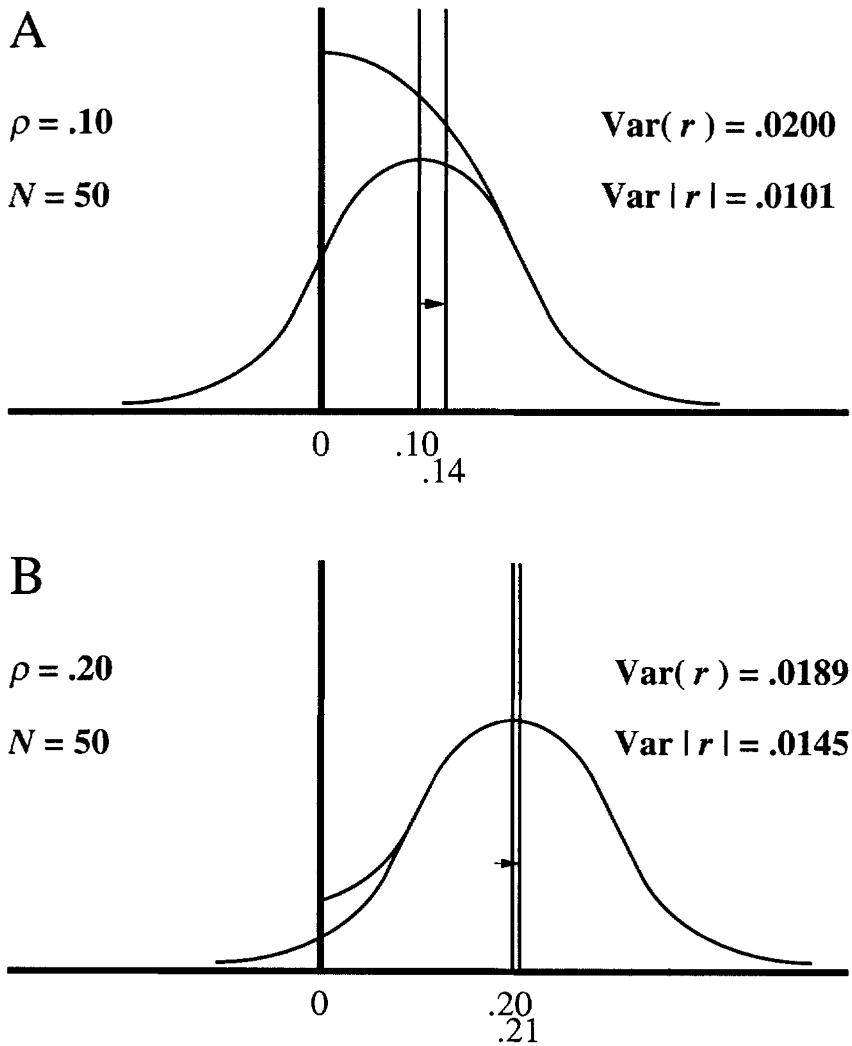

FIGURE 3 Sampling distributions for signed and absolute value correlations, where $N = 50$ and (A) $r = .10$ and (B) $r = .20$.

variance resulting from use of absolute values are reduced. Thus, meta-analytic corrections for the two noted effects lessen as N increases.

Figure 3 shows two sampling distributions where $N = 50$. Parts A and B show distributions where rho is .10 and .20, respectively, rather than 0 as in Figures 1 and 2. Comparison among Figures 1, 3A, and 3B (all of which are for $N = 50$) shows that, as rho increases from 0, both upward bias in the mean and restriction in variance lessen. It is the knowledge of how upward bias in the mean and restriction in variance relate to N and rho that allows for their correction in meta-analysis of absolute value correlations.

DETERMINING UPWARD BIAS IN THE MEAN AND RESTRICTION IN VARIANCE OF $|r|$

Correction for the use of absolute values in meta-analysis requires knowledge of the expected mean and variance of the sampling distributions of both the signed and corresponding absolute value correlations for specified Ns and rhos. The expected mean of the signed correlation is the assumed value of rho. Lacking additional information (e.g., results of a meta-analysis), it is most expedient to assume that rho is zero. This assumption is testable through meta-analysis, however, and may be refined accordingly. The expected variance of the signed correlation (i.e., variability due to sampling error) is given as

$$Var(e) = \left(1 - \rho^2\right)^2 / (N - 1)$$

Again, what ρ (rho) is assumed to be will depend on empirical data. In meta-analysis, ρ is taken to be the weighted mean correlation from independent samples meeting inclusion criteria.

The mean and variance of the distribution of absolute value correlations are difficult to estimate using formulas (especially where rho $\neq 0$). An alternative is to determine the values directly using Monte Carlo simulations. In this approach, sampling distributions are created for signed values (under specific assumptions regarding N and rho) and then "folded over" at zero, thereby making all negative values in a given distribution positive. The mean and variance of the folded distributions may then be determined directly. The reliability of Monte Carlo results depends on the number of point estimates simulated under each combination of assumptions: the greater the number of replications, the more reliable the estimates. In an effort to achieve adequate reliability over a wide range of assumptions, we simulated 100,000 independent correlation point estimates in each of the 7,800 distributions defined by crossing 200 values of N (5 to 1,000 in increments of 5) with each of 39 values of rho (–.95 to .95 in increments of .05).

Knowledge of the means and variances of the sampling distributions for both signed and absolute value correlations allows calculation of the degree of upward bias in the mean and restriction in variance owing to the use of absolute values. As previously noted, upward bias in the mean correlation may be indexed as the difference between the expected signed and absolute value means of the respective sampling distributions. The differences in means for various *N*s and values of rho, representing upward biases, are presented in Table 1. Review of the values in Table 1 shows that, in keeping with Figures 1, 2, and 3, upward bias is reduced as *N* and rho increase.

Also as noted earlier, restriction in the variance of $|r|$ can be indexed as the ratio of the signed (unrestricted) variance to the absolute value (restricted) variance. This ratio may be used to correct the calculation of observed variance in $|r|$ by multiplication of each study's contribution to the observed variance. Hunter and Schmidt (1990a) suggested weighting a study's contribution to observed variance by a factor reflecting *N* as well as other artifacts (e.g., degree of dichotomization in measurement; the greater the dichotomization, the smaller the weight). Where w_i represents a given study's overall weight, variance in the signed *r* is determined as

$$Var(r) = \Sigma\left[w_i\left(r_i - \bar{r}\right)^2\right] / \Sigma w_i$$

In accommodating use of absolute value correlations, the current procedure adds a multiplicative correction factor, c_i, to the numerator of the formula, as follows:

$$Var(r) = \Sigma\left[w_i c_i\left(r_i - \bar{r}\right)^2\right] / \Sigma w_i$$

where r_i = the given study's mean $|r|$ corrected for upward bias and dichotomization (as needed), $\bar{r}$ = the weighted mean of the (doubly) corrected $|r|$ values from all contributing studies, and c_i = the ratio of the variance of signed correlations to the variance of absolute value correlations for the given *N* and rho. Variance correction factors under selected assumptions regarding *N* and rho are summarized in Table 2. As in the case of upward bias, the problem of variance restriction with the use of absolute value correlations is mitigated as *N* and rho increase.

It is important to note that particular values of rho (overall or for any particular study) cannot be known prior to conducting a meta-analysis. The main goal of the meta-analysis is, after all, to estimate rho. It also bears pointing out, however, that the large majority of researchers of trait–performance relations implicitly recognize the potential value of personality to predict job performance and, hence, assume that rho has some nonzero value. That rho may not be zero demands special consideration in meta-analysis of absolute values. Failure to consider this possibility in meta-analysis of personality–performance relations based on absolute values

TABLE 1
Degree of Upward Bias[a] in Absolute Value Correlations for Selected Rhos and Sample Sizes

	Sample Size									
Rho	*5*	*10*	*20*	*35*	*50*	*100*	*140*	*200*	*500*	*1000*
.00	.42	.27	.19	.14	.11	.08	.07	.06	.04	.03
.05	.38	.23	.14	.09	.07	.04	.03	.02	.01	.00
.10	.33	.18	.10	.06	.04	.02	.01	.00	.00	.00
.15	.29	.14	.07	.04	.02	.01	.00	.00	.00	.00
.20	.24	.11	.05	.02	.01	.00	.00	.00	.00	.00
.25	.21	.08	.03	.01	.00	.00	.00	.00	.00	.00
.30	.17	.06	.01	.00	.00	.00	.00	.00	.00	.00
.35	.14	.04	.00	.00	.00	.00	.00	.00	.00	.00
.40	.11	.02	.00	.00	.00	.00	.00	.00	.00	.00
.45	.08	.01	.00	.00	.00	.00	.00	.00	.00	.00
.50	.05	.00	.00	.00	.00	.00	.00	.00	.00	.00
.55	.03	.00	.00	.00	.00	.00	.00	.00	.00	.00
.60	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
.65	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

[a]Tabled values are the differences between rho and mean absolute value correlations (each based on 100,000 independent point estimates).

TABLE 2
Ratios of Expected Variance of Signed Correlations to Expected Variance of Absolute Value Correlations for Selected Sample Sizes, Used to Correct Observed Variance of Absolute Values in Meta-Analysis (= *c*)

	Sample Size									
Rho	*5*	*10*	*20*	*35*	*50*	*100*	*140*	*200*	*500*	*1000*
.00	3.6	3.1	2.9	2.8	2.8	2.8	2.8	2.8	2.8	2.8
.05	3.6	3.0	2.8	2.6	2.5	2.3	2.1	1.9	1.5	1.2
.10	3.5	2.8	2.5	2.2	2.0	1.6	1.4	1.3	1.0	1.0
.15	3.3	2.7	2.1	1.8	1.6	1.2	1.1	1.0	1.0	1.0
.20	3.2	2.4	1.8	1.5	1.3	1.1	1.0	1.0	1.0	1.0
.25	3.0	2.1	1.6	1.3	1.1	1.0	1.0	1.0	1.0	1.0
.30	2.8	1.9	1.4	1.1	1.1	1.0	1.0	1.0	1.0	1.0
.35	2.5	1.7	1.2	1.1	1.0	1.0	1.0	1.0	1.0	1.0
.40	2.3	1.5	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0
.45	2.1	1.3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
.50	1.8	1.2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
.55	1.6	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
.60	1.4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
.65	1.2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
.70	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

will lead to underestimation of the overall predictive power of personality measures. This is because lack of knowledge as to the true value of rho encourages use of the assumption that rho is zero, and corrections to the mean correlation and variance are greatest under this assumption (compare values in the first row of Tables 1 and 2 with subsequent rows). As shown next, the rho = 0 assumption can be challenged and dealt with systematically in providing improved meta-analytic estimates of personality–job performance relations.

For clarity, we begin by describing modified meta-analytic procedures under the expedient but extreme assumption that rho = 0. The proposed modification to standard meta-analysis, which acknowledges the diminishing impact of absolute values as rho differs from zero, is subsequently described and demonstrated using Tett et al.'s (1991) original data set. Comparison between results reported by Tett, Jackson, et al. (1994) and those based on the current procedures permits direct assessment of the effect of the extreme assumption that rho = 0.

META-ANALYSIS OF ABSOLUTE VALUE CORRELATIONS WHERE RHO = 0

Standard meta-analysis allows correction for statistical artifacts at either the level of the individual study (i.e., prior to aggregation of findings across studies) or the aggregate level. The former requires knowledge of artifact characteristics particular to the given study, whereas the latter is accomplished through the use of artifact distributions (i.e., based on any studies reporting the targeted characteristic). Correctable artifacts other than sampling error include those associated with measurement error, range restriction, and dichotomous measurement. Dichotomization (or discontinuity) is most suitably corrected at the study level because its degree can have a strong impact on the correlation, can vary widely between studies, and is usually reported in individual sources (Hunter & Hunter, 1984; Hunter & Schmidt, 1990b; Tett & Meyer, 1993; Tett, Meyer, & Roese, 1994). Similarly, because the effects due to the use of absolute values strongly depend on sample size and because sample size varies greatly between studies and is always provided (studies with unknown *N* are excluded), corrections for those effects are most appropriately implemented at the study level.

Tett et al.'s (1994) procedure included corrections for unreliability, dichotomization, and use of absolute values under the assumption that rho = 0. The entire procedure can be broken down into two steps. Step 1 entails study-level corrections to the mean and variance due to the use of absolute values and to dichotomous measurement. Correction for upward bias in each study's mean absolute value correlation is made by subtracting from it the expected overestimation for the given sample size (e.g., values reported in the first row of Table 1). Note that differences are taken in all cases, not just the originally negative values. This is required because the correction is based on the entire absolute value distribution, which includes both the original positive values and the negative values that have been reflected to be positive. Correction for restriction in observed variance is based on values such as those provided in the first row of Table 2 (again, for rho = 0 and applied to all cases). Step 2 entails the aggregate-level correction for unreliability in both predictor and criterion measures using reliability distributions. (Barrick and Mount, 1991, showed that attenuation due to range restriction was trivial in personality–job performance relations. Hence, correction for that artifact was omitted by Tett et al., 1991, and Tett, Jackson, et al., 1994, and is omitted here.) The partially corrected means and variances from Step 1 are used in the Step 2 calculations. The entire procedure is described step-by-step in the appendix.

META-ANALYSIS OF ABSOLUTE VALUE CORRELATIONS WHERE RHO ≠ 0

The proposed modification to meta-analysis of absolute values acknowledges the implicit assumption of most, if not all, personality-oriented industrial/organizational researchers that rho for personality–job performance relations is not zero. As previously noted, when rho is greater than zero, corrections for upward bias in the mean absolute value correlation and restriction in the corresponding variance are lessened. Our revised method allows the assumption of rho to be refined through *iteration.* In the first iteration, rho is assumed to be zero because, at this point, no other estimate of rho is available and rho = 0 is the most conservative guess. The first round in the proposed procedure is identical to the method employed by Tett, Jackson, et al. (1994), as previously described and in the appendix.

The key logic guiding use of the revised procedure is that, because the rho = 0 assumption is most extreme (i.e., corrections are greatest under it), any resulting mean *r* (i.e., corrected for upward bias) that is greater than zero must be an underestimate of rho. That is, if rho really is zero, then the corrected mean validity from the meta-analysis will be zero (barring random effects of second-order sampling error). The main advantage over the previous procedure (Tett, Jackson, et al., 1994) is that any nonzero mean *r* from a previous iteration is used in the subsequent iteration to correct observed absolute value correlations for upward bias and to correct observed variance for attenuation (e.g., using correction values other than those from row 1 in Tables 1 and 2). Most important, subsequent iterations yield mean validities higher than those from earlier iterations due to use of higher values of rho when making corrections. Differences between iterations in output means and variances will decrease until convergence is achieved (i.e., when adjacent iterations give identical output at a specified level of decimal accuracy). The point of convergence yields the best estimate of the strength and variance of the targeted validity independent of direction.

APPLICATION OF THE PROPOSED ITERATIVE PROCEDURE TO FOUR HYPOTHETICAL DATA SETS

We tested the newly revised procedure using four hypothetical sampling distributions of the signed correlation with known properties: where rho = .1 and .2 crossed with $N = 50$ and 100, each based on 1,000 random point estimates. These cases are relatively simple in that rho and sample size are constant within distributions and the effects of artifacts other than sampling error are ignored. Nonetheless, each case allows an independent evaluation of the main features of the proposed method, in particular, its iterative aspect. In each case, the procedure worked as expected in that, after taking absolute values and running through several iterations of corrections beginning with the most extreme assumption that rho = 0, the resulting mean corrected r and the corrected variance approached asymptotically the values for the original signed distribution (i.e., before taking absolute values; around .1 or .2). We note the following additional observations.

First, the two cases where rho = .2 converged in fewer iterations. This stems from the fact that the effects of absolute values decrease as rho increases. Second, because correction for variance restriction follows estimation of rho, its calculation may be deferred until the final mean corrected $|r|$ has been determined. This saves a step in each iteration but the last. Third, the procedure is self-correcting in that under- or overcorrecting for upward bias in the absolute value correlation (e.g., due to subjective interpolation between tabled values) yields a mean that is, respectively, higher or lower than the value on which the correction is based. Regardless of the direction of the difference (i.e., under- or overcorrection), inconsistency between input and output values guides appropriate modifications to corrections on subsequent iterations, and the procedure continues until convergence is achieved. The most important point to emerge from these demonstrations is that the proposed method correctly recovers the strength of the mean correlation and the variance obtained under the assumption of unidirectionality. Although the calculations are more complex, the procedure provides estimates of rho strength and sampling variance that are directly comparable under both unidirectional and bidirectional assumptions.

APPLICATION OF THE PROPOSED ITERATIVE PROCEDURE TO TETT ET AL.'S (1991) DATA SET

In applying the proposed procedure to Tett et al.'s (1991) overall data set ($K = 97$), convergence was reached at the fourth iteration. Results of each iteration are reported at the top of Table 3 for the main data set. Final moderator results are also provided for the various subgroups compared previously. It bears noting that these results are based on averages across all content areas in personality. They show the

TABLE 3
Revised Meta-Analysis Results for all Samples Combined and for Various Subgroups Under Refined Assumptions Regarding Rho (Numbered Column Headings Detailed at Bottom)

Subgroup	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
All samples																		
Iteration 1[a]	97	13,521	.116	.0069	.118	.0075	.0337	.0262	.0002	.0077	.0260	23	.151	.174	.174	.081	.155	
Iteration 2[b]	97	13,521	.164	.0067	.168	.0073	.0138	.0065	.0003	.0076	.0062	55	.216	.249	.174	.145	.191	
Iteration 3[c]	97	13,521	.170	.0067	.173	.0073	.0118	.0046	.0003	.0076	.0042	64	.223	.257	.174	.152	.195	
Iteration 4[d]	97	13,521	.170	.0067	.174	.0073	.0116	.0044	.0003	.0076	.0040	65	.223	.257	.174	.152	.195	
Exploratory	51	4,467	.101	.0112	.107	.0126	.0029	.0000	.0001	.0127	.0000	100	.138	.159	.035	.092	.122	
Confirmatory	46	9,054	.202	.0047	.204	.0049	.0123	.0074	.0005	.0054	.0069	44	.263	.303	.238	.172	.236	5.38*
No job analysis	39	8,621	.199	.0042	.201	.0044	.0124	.0080	.0005	.0049	.0075	39	.259	.299	.238	.166	.236	
Job analysis	7	433	.259	.0143	.259	.0143	.0070	.0000	.0008	.0151	.0000	100	.333	.384	.250	.197	.321	1.59
Professional	47	3,871	.172	.0117	.181	.0131	.0261	.0130	.0004	.0135	.0126	52	.233	.269	.138	.135	.228	
Nonprofessional	41	8,592	.176	.0044	.177	.0047	.0057	.0010	.0004	.0050	.0006	89	.228	.263	.200	.154	.200	.15
Managerial	16	1,233	.173	.0121	.178	.0133	.0063	.0000	.0004	.0137	.0000	100	.228	.264	.137	.139	.217	
Nonmanagerial	74	11,175	.177	.0062	.181	.0067	.0127	.0060	.0004	.0071	.0057	56	.232	.268	.190	.155	.206	.12
Recruits	12	4,853	.204	.0021	.205	.0023	.0033	.0010	.0005	.0028	.0005	86	.263	.304	.267	.173	.237	
Incumbents	83	8,542	.150	.0094	.155	.0102	.0160	.0058	.0003	.0105	.0055	66	.200	.230	.120	.128	.183	2.29*

Civilian	88	8,467	.145	.0100	.151	.0109	.0151	.0042	.0003	.0112	.0039	74	.193	.223	.110	.125	.176	
Military	9	5,054	.210	.0016	.210	.0017	.0039	.0022	.0005	.0022	.0017	56	.271	.312	.278	.170	.251	2.44*
Subj. criterion	81	11,912	.173	.0064	.177	.0069	.0118	.0049	.0003	.0072	.0046	61	.232	.267	.186	.153	.201	
Obj. criterion	16	1,609	.147	.0093	.149	.0100	.0097	.0000	.0003	.0104	.0000	100	.175	.202	.103	.100	.197	1.04
Researchers	70	10,644	.165	.0061	.167	.0066	.0077	.0011	.0003	.0069	.0008	90	.214	.247	.172	.146	.187	
Company	23	2,334	.189	.0093	.195	.0103	.0291	.0188	.0004	.0107	.0184	37	.251	.290	.173	.126	.265	.77
Articles	61	10,153	.191	.0055	.194	.0059	.0120	.0061	.0004	.0064	.0057	53	.249	.288	.215	.166	.221	
Dissertations	36	3,368	.106	.0105	.110	.0116	.0047	.0000	.0001	.0117	.0000	100	.142	.163	.049	.088	.133	4.62*

Note. Critical z = 1.64 (one-tailed test) for the following comparisons: exploratory vs. confirmatory, no job analysis versus job analysis, recruits versus incumbents, and researchers versus company. Critical z = 1.96 (two-tailed test) for the remaining comparisons; 1 = *K*; number of studies providing data to the given aggregation; 2 = total *N*; the sum of all samples contributing data to the given aggregation; 3 = weighted mean | r | corrected for upward bias; 4 = weighted mean sampling error variance for | r | corrected for upward bias; 5 = weighted mean | r | corrected for both upward bias and discontinuity; 6 = weighted mean sampling error variance for | r | corrected for both upward bias and discontinuity; 7 = variance of | r | corrected for upward bias and discontinuity; Var(r) corrected for restriction; 8 = partial residual variance of rho (= 7 – 6); 9 = variance due to differences in scale reliabilities; 10 = total error variance (= 6 + 9); 11 = total residual variance (= 7 – 10, or = 8 – 9); 12 = proportion of Var(r) due to sampling error and differences in scale reliabilities [= 100 x (10 / 7)]; 13 = weighted mean | r | corrected for upward bias, discontinuity, and criterion unreliability; 14 = weighted mean | r | corrected for upward bias, discontinuity, criterion unreliability, and predictor unreliability; 15 = fully corrected mean r reported previously by Tett et al. (1994); 16 = 95% confidence interval (lower) around the weighted mean | r | corrected for upward bias and discontinuity (around 5); 17 = 95% confidence interval (upper) around the weighted mean | r | corrected for upward bias and discontinuity (around 5); 18 = z-test for the subgroup difference in the weighted mean | r | corrected for upward bias and discontinuity (differences in 5).

[a]rho = .000. [b]rho = .118. [c]rho = .168. [d]rho = .173.

*$p < .05$.

overall power of personality to predict job performance independent of direction. It is also noteworthy that performance criteria included supervisory ratings and objective measures at a ratio of about 5 to 1. Methodological details are reported in Tett et al. (1991).

It is evident at the top of Table 3 that the largest increase in the mean correlation for the overall data set occurs between the first two iterations and that subsequent iterations give rise to smaller increases. This is to be expected because upward bias in the mean and restriction in the variance of absolute value correlations (and corresponding corrections) are greatest at low values of rho. The final iteration produced a mean *r* (corrected for upward bias and dichotomization) of .174, which is notably stronger than the corresponding value from the first iteration (and the one reported by Tett, Jackson, et al., 1994), namely, .118. Another notable feature of the new results is that the fully corrected mean *r* for confirmatory studies, .303, is considerably higher than the .238 value reported previously by Tett, Jackson, et al. (1994). Such differences show the limitations of using the extreme and rigid assumption that rho = 0 versus an assumption that is suitably responsive to observed results from previous iterations.

Results of the revised moderator analyses reveal overall stronger mean validities than those reported previously, but they are otherwise largely unchanged with respect to the role of moderators. Thus, validities based on confirmatory strategies, recruits, and/or military personnel and those reported in articles are significantly stronger than validities based on exploratory strategies, incumbents, and/or civilian samples, and those reported in dissertations, respectively. The difference for the use of job analysis versus no job analysis ($z = -1.59$) approaches significance at the .05 level, favoring use of job analysis. Further research on the potential benefit of using trait-based job analysis over other confirmatory strategies may prove worthwhile.

We note that the use of absolute values may seem counterintuitive in the case of personality–performance relations based on confirmatory strategies: confirmatory studies more clearly specify the expected direction of the targeted relation, so use of absolute values appears unnecessary. Three considerations led us to use absolute values (with corrections) in the current analyses involving confirmatory studies. First, a major point of Tett et al.'s (1991) original meta-analyses was to compare results from confirmatory versus exploratory studies. Exploratory studies demand use of absolute values in meta-analysis because they do not specify the direction of personality–performance relations (i.e., meaningful negative and positive values will cancel each other out, thereby underestimating the value of personality in the prediction of job performance). Absolute values were used in the case of confirmatory studies to facilitate comparisons between the results from the two types of study. Second, we wished to compare current findings with those derived previously (Tett, Jackson, et al., 1994) based on incomplete methods. Use of absolute values in the earlier aggregations of confirmatory findings called for similar treatment here to demonstrate more readily the effect of iteration. Finally, as shown using the four hypothetical sampling distributions, the current procedure recovers the correlation mean and variance based on signed values. Use of absolute values with appropriate corrections, although entailing more laborious calculations, gives unbiased results for confirmatory as well as exploratory findings. Notwithstanding the importance of these considerations in the this undertaking, future meta-analyses may be less dependent on use of absolute values as results of confirmatory studies in this area continue to accumulate.

DISCUSSION

Standard meta-analysis (Hunter & Schmidt, 1990a) was developed largely in the context of relations between cognitive ability and job performance, where all population values are assumed to be positive and all negative observed values are attributed to sampling error. The presence of negative population values under this unidirectionality assumption will systematically underestimate effect sizes. Moreover, because the extent of negative bias cannot be estimated, meta-analytic results will be substantially uninterpretable.

The complexity of personality and its potential role in work settings encourages consideration of the possibility of bidirectional relations with job performance (i.e., positive in some settings and negative in others). Evidence from both single sample and meta-analytic research supports the view that personality–job performance relations can vary in direction meaningfully as a function of situational factors rarely reported in source studies. If the overall value of personality in the prediction of performance is to be known, it is critical that meta-analysis of personality–performance linkages takes account of such bidirectionality. The approach advocated here is to use absolute value correlations with appropriate corrections for known distortions in the mean and variance of observed distributions. Application of this procedure to our 1991 data set produced a substantially stronger and, we believe, more realistic estimate of the strength of the relation between personality and job performance.

It is important to note that, under both uni- and bidirectionality assumptions, the proposed extension of standard meta-analysis does not systematically bias estimates of rho and variance. If rho is in fact zero, then the first iteration will reveal a weighted mean *r* of zero and convergence will be obtained immediately. It should also be noted that the corrections to both observed *r* and observed variance of *r* are directly linked to the assumed rho and sample size. Given the noted reliability of the Monte Carlo simulations (i.e., based on 100,000 replications at each combination of assumptions about rho and *N*), corrections can be considered exact.

It also bears repeating that, in a hypothetical ideal world, use of absolute values in meta-analysis may not be the most desirable approach to aggregating bidirectional relations. Possibly, a more appropriate method would be to use standard moderator analysis involving either subgroup comparisons or moderator correlations (i.e., where continuous moderator variables are correlated with effect sizes). Use of those methods, however, would require (a) clearly articulated theoretical reasons for expecting positive versus negative relations for particular traits and job settings (e.g., in terms of job tasks, work groups, organizational culture, or some combination thereof), (b) quantifiable indices of those bases for directional differences, and (c) sufficient numbers of studies reporting those indices reliably to offset the effects of second-order sampling error. Each of these conditions is currently far from being met, encouraging use of absolute values with associated corrections.

As studies continue to report meaningful negative trait–performance relations (e.g., between Conscientiousness facets and positively keyed aspects of job performance; Bunce & West, 1995; Driskell et al., 1994; R. Hogan & J. Hogan, 1995; J. Hogan et al., 1992), the need for explanations for bidirectionality will increase, and testable hypotheses are likely to be developed. Efforts need to be directed toward identifying key study characteristics (e.g., tasks, groups, culture) and to reporting that information in source studies. Only when testable rationales exist and sufficient numbers of studies containing the required information are available will standard meta-analysis be suitable for assessing the overall predictive potential of personality measures. Until then, use of absolute values with associated corrections seems the most viable alternative.

Implications for Previous Meta-Analyses of Personality–Job Performance Relations

Recognition of the possibility of bidirectional relations between personality and job performance suggests alternative interpretations of results from meta-analyses of personality relations that have ignored that possibility. As we have emphasized throughout our article, the available evidence for bidirectionality suggests that meta-analyses based on an assumption of unidirectionality will underestimate the overall importance of personality in predicting job performance (irrespective of direction) owing to cancellation of (true) positive and negative validities. This holds even in cases applying general taxonomies of personality traits, performance dimensions, and job families. Some may find this counterintuitive because the purpose of such taxonomies is to organize validities into narrower subclasses where unidirectionality may appear to be a more reasonable assumption. It is a debatable assumption, however, because variables other than the broad classifications may affect the direction of the validity coefficient. For example, extraversion could predict sales performance positively in some jobs (e.g., those requiring a gregarious and energetic sales style), but negatively in others (e.g., those requiring a reserved and soft-spoken approach). Meta-analysis based on the assumption of unidirectionality in this case would underestimate the overall usefulness of extraversion to predict sales performance (i.e., regardless of direction). (It is notable in this light that Extraversion has been shown in two mutually exclusive meta-analyses to correlate in opposite directions with sales performance [i.e., .09 in Barrick & Mount, 1991; –.07 in Salgado, 1997].)

Results of previous meta-analyses of personality–performance relations based on unidirectional assumptions warrant review from the perspective of relation strength. Barrick and Mount (1991), for instance, found substantial residual variance (i.e., more than 25% unattributable to artifacts) in validities across studies in 13 out of 15 aggregations using broad trait, criterion, and job taxonomies. As would be expected with the presence of true negative validities, the relatively high variances are coupled with low mean correlations for the Big Five dimensions (e.g., range = .02 for Openness to Experience to .15 for Conscientiousness in predicting ratings, averaging across job groups). An important conclusion of Barrick and Mount is that "one dimension, Conscientiousness, showed consistent relations with all job performance criteria for all occupational groups" (p. 1). Two other dimensions, Extraversion and Openness to Experience, were related to performance in a few subclassifications, but these values were modest (range = .09 to .15). It is interesting to note that averaging across trait and job dimensions within job proficiency criteria in Barrick and Mount's study yields an overall validity of .055, which is less than one third the strength of the corresponding value obtained here (i.e., .174). Looking to studies employing a confirmatory strategy, we see a mean of .204, nearly four times Barrick and Mount's net result. Thus, the assumption of unidirectionality can yield an average validity that seriously underestimates the importance of personality in the prediction of job performance.

An important outcome of the unidirectionality assumption in meta-analyses of personality–job performance relations has been to advance a relatively simple view of the role of personality in the workplace. Barrick and Mount's (1991) findings have spawned considerable productive investigation into the roles of Conscientiousness and, to lesser degrees, Extraversion and Openness, because those dimensions showed the most positive and consistent relations with work criteria. Such follow-up research is entirely warranted, and we welcome more of it. It would be unfortunate, however, if researchers were to ignore the potentially greater richness afforded by a bidirectional view of personality at work. We suggest, based on the evidence presented here, that bidirectionality is a prominent feature of personality–job performance relations. A critical need at this juncture is theory specifying the conditions under which a selected trait might be expected to relate positively versus negatively with important work outcomes. Guided by theory—perhaps one derived within an interactionist framework—trait-oriented job analysis that is sensitive to the bipolar nature of personality variables offers a reasonable basis for discovering those conditions.

Where previous meta-analyses of personality–job performance relations have ignored both the value of confirmatory research (at the individual study level) and the possibility of bidirectional relations, it would be hazardous to interpret the low levels of their mean validities as reflecting the true potential for personality in predicting job performance. The picture, in fact, is far less gloomy. As theory linking personality and performance continues to develop and systematic bases for differences in the direction of those relations are identified, we remain optimistic that corresponding validities will improve and understanding of the role of personality in the workplace will be advanced.

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APPENDIX

Summary of Revised Meta-Analysis Procedure

The proposed meta-analysis of absolute value correlations is derived from procedures outlined by Hunter and Schmidt (1990a and 1990b). Step 1 entails study-level corrections for discontinuity and use of absolute values. Step 2 entails aggregate-level correction for unreliability in both predictor and criterion measurement using artifact distributions. The partially corrected means and variances from Step 1 are used in the Step 2 calculations. The entire procedure is repeated iteratively, beginning with the conservative assumption that rho = 0 and continuing with refined estimates of rho from previous iterations. Estimates of rho directly affect Step 1b for correcting the mean $|r_i|$ for upward bias at Step 1c, and Step 1l for disattenuating observed Var $|r|$ at Step 1m.

Step 1: Study-Level Corrections for Dichotomization and Use of Absolute Values

a. Calculate the within-sample mean observed $|r_i|$ by averaging the absolute values of all useable *r*s within each sample meeting inclusion criteria.

b. For each sample, determine the expected absolute value correlation, E$|r_i|$, based on *N* and the assumed value of rho (from Table 1).

c. For each sample, subtract the expected absolute value correlation, E$|r_i|$, from the mean observed absolute value correlation, $|r_i|$, to provide an estimate of r_i.

$$r_i = |r_i| - \mathrm{E}|r_i|$$

d. For cases involving dichotomous measurement, compute the dichotomization correction factor, a_i, based on p and q. For cases not involving dichotomization, $a_i = 1$. (See Hunter & Schmidt, 1990b, p. 335.)

e. Compute each sample's weight:

$$w_i = N_i a_i^2$$

f. Compute the sum of the weights across samples, Σw_i.

g. Compute the weighted mean r uncorrected for dichotomization:

$$\bar{r} = E(w_i r_i) / \mathrm{E}w_i$$

h. Compute each sample's sampling error variance for r_i uncorrected for dichotomization:

$$\mathrm{Var}(e_i) = (1 - \bar{r}^2)^2 / (N_i - 1)$$

i. Compute the weighted mean sampling error variance for r uncorrected for dichotomization:

$$\mathrm{Var}(e) = \mathrm{E}[w_i \mathrm{Var}(e_i)] / \mathrm{E}w_i$$

j. Correct each r_i for dichotomization:

$$r_i' = r_i / a_i$$

k. Compute the weighted mean r' corrected for upward bias and dichotomization:

$$\bar{r}' = \mathrm{E}(w_i r_i') / \mathrm{E}w_i$$

l. For each sample, determine the correction ratio, c_i, for disattenuating variance of $|r_i|$, based on N and the assumed value of rho (from Table 2).

m. Compute the weighted variance of r' corrected for dichotomization and use of absolute values:

$$\mathrm{Var}(r') = \mathrm{E}[w_i c_i(\bar{r}_i' - r')^2] / \mathrm{E}w_i$$

n. Compute each sample's sampling error variance for r_i' corrected for dichotomization:

$$\mathrm{Var}(e_i') = \mathrm{Var}(e_i) / a_i^2$$

o. Compute the weighted mean sampling error variance for the corrected r':

$$\mathrm{Var}(e') = \mathrm{E}[w_i \mathrm{Var}(e_i')] / \mathrm{E}w_i$$

p. Compute the partial residual variance of observed correlations:

$$\text{partial residual } \mathrm{Var}(r) = \mathrm{Var}(r') - \mathrm{Var}(e')$$

Step 2: Aggregate-Level Correction for Unreliability

a. Assemble predictor (x) and criterion (y) reliability distributions based on available values and calculate the following:

i) $mean\sqrt{r_{xx}}$

ii) $SD\sqrt{r_{xx}}$

iii) $mean\sqrt{r_{yy}}$

iv) $SD\sqrt{r_{yy}}$

b. Calculate the mean attenuation factor (MAF) for predictor and criterion unreliability:

$$MAF = mean\sqrt{r_{xx}} \cdot mean\sqrt{r_{yy}}$$

c. Correct the weighted mean r' (corrected for dichotomization and use of absolute values in Step 1) for predictor and criterion unreliability:

$$\bar{r}'' = \bar{r}' \,/\, MAF$$

d. Calculate the squared coefficient of variation (CV^2) for the predictor and criterion measures:

$$CV_x^{\,2} = \left(SD\sqrt{r_{xx}} \,/\, mean\sqrt{r_{xx}}\right)^2$$

$$CV_y^{\,2} = \left(SD\sqrt{r_{yy}} \,/\, mean\sqrt{r_{yy}}\right)^2$$

e. Calculate the variance due to differences in predictor and criterion reliability:

$$\text{measurement Var}(e) = \bar{r}''^2 \cdot \text{MAF}^2 \cdot (CV_x^2 + CV_y^2)$$

f. Calculate the variance due to all artifacts:

$$\text{total Var}(e) = \text{Var}(e') + \text{measurement Var}(e)$$

g. Calculate the total residual variance of observed correlations:

$$\text{total residual Var}(r) = \text{Var}(r') - \text{total Var}(e)$$

h. Calculate the proportion of Var(r') due to total Var(e):

$$\% \; Var(r') = 100 \cdot [\text{total } Var(e) \, / \, Var(r')]$$

i. Correct the weighted mean r' (corrected for upward bias and dichotomization in Step 1) for criterion unreliability only:

$$\text{partially corrected } \bar{r}'' = \bar{r}' \, / \, mean\sqrt{r_{yy}}$$

j. Calculate second-order sampling error based on mean r' (corrected for upward bias and dichotomization in Step 1):

$$Var(\varepsilon) = Var(r') \, / \, K$$

where K = the number of contributing samples.

k. Calculate the 95% confidence interval around the weighted mean r' (corrected for upward bias and dichotomization in Step A):

$$95\% \; CI = r' \pm 1.96\sqrt{Var(\varepsilon)}$$

l. Conduct a z test for subgroup differences in the weighted mean r' (corrected for upward bias and dichotomization in Step 1):

$$z = (\bar{r}_1' - \bar{r}_2') \, / \, \sqrt{[Var(r_1') \, / \, K_1] + [Var(r_2') \, / \, K_2]}$$

where K = the number of contributing samples per subgroup.