The relation between emotional intelligence and job performance: A meta-analysis

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Summary
This meta-analysis builds upon a previous meta-analysis by (1) including 65 per cent more studies that have over twice the sample size to estimate the relationships between emotional intelligence (EI) and job performance; (2) using more current meta-analytical studies for estimates of relationships among personality variables and for cognitive ability and job performance; (3) using the three-stream approach for classifying EI research; (4) performing tests for differences among streams of EI research and their relationships with personality and cognitive intelligence; (5) using latest statistical procedures such as dominance analysis; and (6) testing for publication bias. We classified EI studies into three streams: (1) ability-based models that use objective test items; (2) self-report or peer-report measures based on the four-branch model of EI; and (3) “mixed models” of emotional competencies. The three streams have corrected correlations ranging from 0.24 to 0.30 with job performance. The three streams correlated differently with cognitive ability and with neuroticism, extraversion, openness, agreeableness, and conscientiousness. Streams 2 and 3 have the largest incremental validity beyond cognitive ability and the Five Factor Model (FFM). Dominance analysis demonstrated that all three streams of EI exhibited substantial relative importance in the presence of FFM and intelligence when predicting job performance. Publication bias had negligible influence on observed effect sizes. The results support the overall validity of EI. Copyright © 2010 John Wiley & Sons, Ltd.

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Introduction

Emotional intelligence (EI) has received a substantial amount of attention in the Organizational Behavior, Human Resources, and Management (OBHRM) literatures in recent years from those who champion its use and others who are wary of its validity. There has also been considerable popular...
interest in EI, and books on EI have been best-sellers (Goleman, 1995; Goleman, Boyatzis, & McKe, 2002). Much of the upsurge in use is attributable to favorable reports of the predictive and construct validity of EI (e.g., Ashkanasy & Daus, 2005; Brackett & Mayer, 2003; Brackett, Mayer, & Warner, 2004; Daus & Ashkanasy, 2005; Dulewicz & Higgs, 2000; Dulewicz, Higgs, & Slaski, 2003; Fox & Spector, 2000; Law, Wong, & Song, 2004), and the resurgence of interest in personality research (Hough & Ones, 2001; Judge, Bono, Ilies, & Gerhardt, 2002). Recent research highlights the importance of EI as a predictor in important domains such as academic performance, job performance, negotiation, leadership, emotional labor, trust, work–family conflict, and stress (Ashkanasy & Daus, 2002; Fulmer & Barry, 2004; Humphrey, 2002, 2006; Humphrey, Pollack, & Hawver, 2008; Jordan, Ashkanasy, & Hartel, 2002). The major purpose of this meta-analysis is to extend these prior studies by testing whether EI accounts for unique variance in predicting job performance above and beyond the Five Factor Model (FFM) and cognitive ability.

Although a variety of concepts similar to EI have been proposed over the years (Ashkanasy & Daus, 2005), modern interest in EI began with Salovey and Mayer’s (1990) article defining EI. Later, Mayer and Salovey (1997) revised their definition of EI into their four-branch model of EI. In order to meet traditional definitions of “intelligence,” Mayer, Salovey, and Caruso (2002) developed the Mayer–Salovey–Caruso Emotional Intelligence Test (MSCEIT). This was followed by the MSCEIT V2.0, which Mayer, Salovey, Caruso, and Sitarenios (2003: 99) described as a “141-item scale designed to measure the following four branches (specific skills) of EI: (1) perceiving emotions, (2) using emotions to facilitate thought, (3) understanding emotions, and (4) managing emotions.” However, a number of other scholars and practitioners developed measures of EI that used self-report or peer ratings, and some used broader definitions of emotional competencies that included measures of related personality traits or skills. In their prior meta-analysis, Van Rooy and Viswesvaran (2004: 72) conceptualized EI as “the set of abilities (verbal and nonverbal) that enable a person to generate, recognize, express, understand, and evaluate their own, and others, emotions in order to guide thinking and action that successfully cope with environmental demands and pressures.”

Some measures that recent validity studies have examined include the Bar-On Emotional Quotient Inventory (EQ-i), Emotional Intelligence Scale (EIS, Schutte et al., 1998), Work Profile Questionnaire-Emotional Intelligence Version (WPQ-EI, Cameron, 1999), and the MSCEIT V2.0 (Mayer, Caruso, & Salovey, 1999; Mayer et al., 2003). Additional work is being conducted by Wong and Law (WLEIS, 2002) to validate a shortened 16-item measure of EI. In addition, Jordan, Ashkanasy, Hartel, and Hooper (2002) developed the Workgroup Emotional Intelligence Profile (WEIP); in a series of studies they demonstrated that the WEIP is distinguishable from a variety of personality scales, such as the 16 Personality Factors, the Revised Self-monitoring Scale, and the Personal Style Inventory. The work that researchers such as Keele and Bell (2007), Van Rooy and Viswesvaran (2004), Law et al. (2004), and Rode et al. (2007), have done on the construct validation of the EI concept will eventually enable the field to reach a consensus, but much more work is still needed. Specifically, more research needs to be conducted to assess the validity of ability-based measures of EI (e.g., MSCEIT V2.0) as compared to self-report measures (e.g., WLEIS) or other methods of measuring EI. Thus, one of the major purposes of this meta-analysis is to compare how these different methods of measuring and conceptualizing EI predict job performance. To guide our analysis, and to compare these different methods, we organize the empirical literature using the Ashkanasy and Daus (2005) categorization of the three streams of EI research.

A second major purpose of this research is to investigate whether EI measures incrementally predict job performance when measures of personality and cognitive intelligence are also included as predictors. Personality measures such as the FFM have been shown to be excellent predictors of important work-related variables, such as transformational and transactional leadership (Bono & Judge, 2004), as well as leadership emergence and leader performance (Judge et al., 2002). The Five
Factor personality variables may also be related to the performance of emotional tasks at work such as performing emotional labor and emotional regulation (Bono & Vey, 2007). Meta-analysis has also confirmed that cognitive ability is an important predictor of work-related outcomes such as leadership (Judge, Colbert, & Ilies, 2004) and, to date, cognitive intelligence is the single best predictor of job performance (Schmidt, Shaffer, & Oh, 2008).

Some researchers have questioned whether EI measures add incremental validity to more established constructs such as the FFM of personality and general mental ability (GMA) (e.g., Conte, 2005; Landy, 2005; Locke, 2005; Newsome, Day, & Catano, 2000; Schulte, Ree, & Caretta, 2004, Van Rooy, Alonso, & Viswesvaran, 2005). However, a number of studies have shown that EI does add incremental predictive validity beyond GMA and the FFM with regards to a variety of issues such as individual performance (Rode et al., 2007) and work–family conflict (Lenaghan, Buda, & Eisner, 2007).

Van Rooy and Viswesvaran (2004) conducted a meta-analysis to assess incremental validity and arrived at mixed, but generally favorable, conclusions toward EI. As Van Rooy and Viswesvaran observed, very few studies have been done on EI and job performance at the time of their data gathering, so they included a wide variety of non-work outcomes in their meta-analysis, including lab studies, academic outcomes (primarily GPAs), sports such as hockey and basketball, health outcomes, and various other outcomes. Only 19 out of the 59 independent samples in their overall EI meta-analysis were done in employment settings (these 19 samples included 28 per cent of the participants in the 59 samples), thus the results of their meta-analysis are weighed heavily toward non-work settings (see Table 1 in Van Rooy & Viswesvaran, 2004: 81). When they separated the employment samples from the non-work ones, they found that EI predicted performance in work settings. However, because of their small number of total studies, they combined the employment and non-employment studies when examining EI’s relationship to cognitive intelligence and other personality factors, and when examining the incremental validity of EI. Perhaps because of their smaller sample size, Van Rooy and Viswesvaran (2004: 86) only examined the incremental validity of EI compared to each of the five personality traits in the FFM at one a time, thus their meta-analysis did not examine whether EI predicts performance over the entire set of FFM. Moreover, they did not examine whether EI shows incremental validity when controlling for cognitive intelligence and the FFM simultaneously.

In addition, since Van Rooy and Viswesvaran (2004) gathered their data, EI researchers have developed new scales to address the criticisms and shortcomings of the early measures, or refined their preliminary ones. For example, their study includes the early EI scale developed by Mayer and Salovey (1997), the MEIS, but not the improved and now commonly used MSCEIT scales (Mayer et al., 2002). Likewise, researchers have also developed new self-report scales such as the WEIP (Jordan, Ashkanasy, Hartel, & Hooper, 2002).

A more recent meta-analysis by Joseph and Newman (2010) tested the incremental validity of EI measures to explain job performance over and above the Big Five personality measures and cognitive ability. They classified EI measures into three categories: performance based, self-report ability measures, and self-report mixed models. They found that all three types of EI measures demonstrated incremental validity over and above the Big Five personality traits. In addition, all three have incremental validity above cognitive ability. Only the two self-report EI measures have incremental validity over and above both the Big Five Factors and cognitive ability. They concluded that for overall job performance that performance-based measures of EI are redundant with personality and cognitive ability. However, when they examined incremental validity for jobs high in emotional labor demands, they found that all three types of EI measures have incremental validity over and above both personality and cognitive ability. Joseph and Newman (2010) also tested for subgroup differences in EI and found that performance-based ability tests showed a roughly one standard deviation (−0.99) difference that favored Whites over Blacks. However, because of the small number of studies that reported race they suggested that more studies need to be done on this before determining if adverse impact exists. The
authors also developed a “cascading model” that related specific facets of EI and cognitive ability, conscientiousness, and emotional stability to job performance.

Overall, the previous meta-analyses on the EI construct have been beneficial for the literature. However, the present research builds upon extant research in six ways. First, we include a larger number of studies to achieve more reliable point estimates of the incremental validity of EI for job performance. Compared to the Joseph and Newman (2010) study, our data set includes 65 per cent more studies that examine the relationship between EI and job performance, with an $N$ that is over twice as large. Although the Joseph and Newman study was recently published, it was based (according to a footnote in their paper) on research that they presented at a 2007 conference, and with the tremendous growth in the field of EI a substantial number of high quality studies have been published in the last few years. And, as we illustrate in the results section, including these newer studies (which more often use the latest scales available) substantially changes the estimates of incremental validity and the overall relationship between EI and job performance.

Second, we use the latest published meta-analyses to obtain our estimates of other relationships such as the relationships between cognitive intelligence and job performance. This is important because these estimates are used to calculate the incremental validity of EI over personality and cognitive intelligence. For example, the Joseph and Newman study used the Hunter and Hunter (1984) study to estimate the relationship between cognitive intelligence and job performance, whereas we use the more recent meta-analysis of this relationship done by Schmidt et al. (2008). Moreover, Joseph and Newman use the Ones (1993) study to estimate the intercorrelations among the Big Five, whereas we use more recent meta-analyses from Mount, Barrick, Scullen, and Rounds (2005). These more recent meta-analyses have larger sample sizes and include studies with the latest available research methodologies. The more recent study by Schmidt and colleagues gives a higher estimate of the relationship between cognitive intelligence and job performance compared to Hunter and Hunter (1984). Using the most current estimate is a more conservative approach that sets a higher bar for demonstrating the incremental validity of EI measures. In order to prove the value of EI to cognitive ability researchers, it is crucial that a meta-analysis pass this higher bar when demonstrating incremental validity.

The third way in which the present research expands the literature is by using the Ashkanasy and Daus (2005) theoretical model to examine the three main streams of EI research (i.e., ability-based, self-reports based on the ability models, mixed models). We review the literature that shows that there are important theoretical distinctions among the three streams. Although Joseph and Newman (2010) examined three types of EI measures that were similar in many ways to the three streams of EI research in Ashkanasy and Daus's model, Joseph and Newman did not specifically draw upon the Ashkanasy and Daus theoretical model. Moreover, they concluded that the self-report ability measures may not be any different from mixed models on either theoretical or empirical grounds. In contrast, we draw explicitly upon the Ashkanasy and Daus (2005) theoretical model to make important distinctions among the three streams. We illustrate how each stream individually, as well as collectively, predicts job performance.

Fourth, Joseph and Newman (2010) conclude that there are little differences empirically between self-report ability EI and self-report mixed EI in how they relate to personality variables; however, they do not specifically test for these differences. In contrast, we explicitly test whether each stream has the same correlations with the five personality factors and with cognitive ability. We found, with our larger and more comprehensive data set, that there are important differences among the three streams as theorized.

The fifth way in which the present research expands the literature is via the use of a newer statistical technique: dominance analysis. By using dominance analysis, which was first proposed by Johnson (2000), we can gain better estimates of the relative importance of EI, cognitive ability, and the FFM in the prediction of job performance. We expect that all three sets of variables will make substantively important contributions to the explanation of job performance. Sixth, we use the latest techniques to...
test and correct for publication bias. The Joseph and Newman (2010) study did not use dominance analysis or test for publication bias.

The present research proceeds as follows. In the following section, we describe, in detail, Ashkanasy and Daus’s (2005) classification of the research on EI into three streams. Then, we examine the degree to which EI measures should be positively or negatively related to GMA and various personality traits. We argue that some measures of EI should be more closely related to specific personality traits than others. We, then, discuss the reasons why all three types of EI measures should incrementally predict job performance and summarize our literature review by presenting our hypotheses.

Three Streams of EI Research

Ashkanasy and Daus (2005: 441) reviewed the extant data on EI and classified the research into three streams: “(1) a four-branch abilities test based on the model of EI defined in Mayer and Salovey (1997); (2) self-report instruments based on the Mayer–Salovey model; and (3) commercially available tests that go beyond the Mayer–Salovey definition.” The third stream of research is also known as the mixed model because it includes traditional social skill measures as well as EI measures. Ashkanasy and Daus (2005) argued that there are important theoretical and methodological reasons to distinguish among the three streams. In particular, they argued that many of the criticisms directed at the field of EI research – such as overlaps between EI measures and other personality traits – are inappropriately directed at all three streams of research. They argued that these overlaps occur primarily within the third stream of research (and also in the earliest versions of EI measures). Researchers in the third stream have developed comprehensive measures such as the ECI and the Bar-On measures that included social skills and abilities, whereas the researchers in the Mayer–Salovey tradition have developed more narrow measures that focus on perceiving emotions, understanding emotions, and regulating emotions. In particular, the ability-based measures were specifically developed to guard against charges of excessive overlaps and redundancies with existing personality measures. Some overlap is, of course, reasonable and could even be a sign of construct validity because EI should relate to personality variables such as emotional stability. The problem would be if the correlations were high enough to indicate that EI was measuring the same underlying traits as the FFM. Consequently, it is important to test whether the three streams do, in fact, differ in their correlations with personality traits.

Although Ashkanasy and Daus (2005) think the mixed models may have conceptual overlaps with other measures, they acknowledged that these measures may, in fact, do an excellent job predicting performance. Cherniss (2010) also notes that mixed models may have greater predictability. As Jordan, Dasborough, Daus, and Ashkanasy (2010) reason, these stream three measures include components of personality, attitudes, and personal preferences, so it is natural that these broader measures capture more variance. However, this broader nature makes it harder to understand how much of the explained variance is due to EI and how much to the other components of the measures. The self-report stream 2 research based on Mayer and Salovey may also differ from the ability measures in important ways. Even though Ashkanasy and Daus think highly of both stream 1 ability measures and stream 2 self-report measures, they note that some emotions researchers strongly prefer self-report measures:

Ashton-James (2003), for example, while agreeing with the overall theoretical basis of emotional intelligence (as in Ashkanasy et al., 2004), has criticized the abilities measures of emotional intelligence on the basis that they can do no more than tap respondents’ semantic knowledge about emotion. For Ashton-James, a true measure of emotional intelligence must place respondents in a context where they can actually experience the emotions that they are asked to respond to. (p. 448)
Researchers who use self-reports may better capture the emotions that employees are actually feeling in the workplace. Because the FFM also uses self-report measures that ask respondents to measure their actual behavior, it is possible that self-report measures (both streams 2 and 3) of EI would correlate slightly (but significantly) more with these personality measures than would stream 1 ability measures. Because stream 3 measures overlap both in their measurement method and in the content of their questions, while stream 2 measures only overlap with regard to the use of self-reports, stream 3 measures should show higher relationships with personality factors than stream 2 measures. As Jordan et al. (2010) argue, stream 3 measures, unlike stream 2, include measures of personality factors not directly related to EI, so it is likely that these measures will overlap more with similar personality measures.

The MSCEIT was also developed to meet criticisms that EI is not intelligence as measured by right or wrong answers, as in a traditional cognitive intelligence test. Consequently, the MSCEIT uses an “objective” style test with right or wrong answers; the accuracy of the answers is determined by either consensus judgments or expert judgments, with the two methods correlating highly with each other (Mayer et al., 2003). Although this method of measuring EI may produce the purest measure of EI and the least overlap with personality measures, it may correlate more with traditional cognitive measures. A moderate correlation may also show construct validity and indicate that EI is a form of intelligence, because various measures of intelligence (such as math and verbal skills) are usually positively correlated. However, for this measure and the other measures of EI to be of any use they would need to add incremental validity to job performance beyond measures of GMA and other personality measures.

Emotional Intelligence and Performance

Although there is considerable debate among the advocates of the three different streams of EI research, there is good reason to believe that all three types of measures predict job performance. All three streams of research measure at least part of the core concepts behind EI, and it is likely that the ability to recognize emotions in one’s self and in others contributes to effective social interaction, as does the ability to regulate one’s own emotions. Even in contexts that are normally highly cognitive in nature, such as classrooms and colleges, EI may contribute to performance by helping with group tasks. Offermann, Bailey, Vasilopoulous, Seal, and Sass (2004), for example, found that EI better predicted performance on student teamwork projects and on ratings of leadership, whereas a cognitive ability measure better predicted student performance on individual cognitive tasks like tests. Likewise, in an assessment center study that gave participants the chance to work on cognitively complex or simple tasks, Kellett, Humphrey, and Sleeth (2002, 2006) found that both cognitive and EI measures predicted leadership emergence. The relative importance of EI and cognitive ability may depend on the cognitive complexity of the job being performed (Côté & Miners, 2006). In almost all work settings, individuals have to cooperate with others and do at least some group work tasks.

EI may be especially important in the service sector and in other jobs where employees interact with customers. In a food service setting, Sy, Tram, and O’Hara (2006) directly related the EI of the leaders to their ability to manage the job satisfaction of their subordinates. In a similar study, although not directly on EI, Bono, Folds, Vinston, and Muros (2007) found that transformational leaders helped their employees remain in a positive mood while interacting with each other and with customers. It is likely that leaders high on EI would be better at helping their employees maintain positive moods while interacting with customers and performing emotional labor. Emotional labor occurs when employees must alter their emotional expressions in order to meet the display rules of the organization (Ashforth & Humphrey, 1993; Diefendorff, Croyle, & Gosserand, 2005; Hochschild, 1979; Pugh, 2001; Rafaeli &
Sutton, 1990). The importance of emotional labor to job performance is even greater now that the service sector of the economy has grown while the manufacturing sector has declined (Bono & Vey, 2007). Emotional labor may be stressful for some employees (Bono & Vey, 2005), especially those lacking in autonomy (Grandey, Fisk, & Steiner, 2005), and the ability to regulate one’s emotions may help employees cope with this stress.

The ability to recognize emotions in others may help one know when to perform emotional labor, just as the ability to recognize one’s own emotions may help employees know when they need to pay attention to altering their emotional expressions. Brotheridge (2006: 139) found “the key role of emotional intelligence seemed to be as a predictor of the perceived situational demands, which, in turn, predicted the nature of emotional labor that was performed.” She found that employees with high EI were more likely to perceive displaying emotions as part of their job and to use deep acting. Joseph and Newman (2010) meta-analysis found that EI was a better predictor of performance for jobs that required emotional labor than for jobs overall.

Although emotional labor has been conceptualized primarily in terms of service work, leaders high on EI may perform emotional labor in order to influence the moods, motivations, and performance of their team members (Humphrey, 2008; Humphrey et al., 2008). Finally, the prior meta-analysis performed by Van Rooy and Viswesvaran (2004) provides empirical support for the notion that EI predicts performance, although this needs to be confirmed using the latest measures and studies while controlling for personality and GMA.

Our hypotheses are:

**Hypothesis 1a:** As a set, collectively, all three EI streams are significantly and positively correlated with job performance.

**Hypothesis 1b:** Individually, each EI stream is significantly and positively correlated with job performance.

**Hypothesis 2:** EI is positively related to extraversion, openness, agreeableness, conscientiousness, and cognitive ability and negatively related to neuroticism.

**Hypothesis 3a:** Stream 1 measures of EI are more strongly related to cognitive ability relative to stream 2 and stream 3 measures.

**Hypothesis 3b:** Stream 1 measures will show the lowest relationships with personality measures, stream 2 measures the next lowest, and stream 3 measures the highest relationships with personality measures.

**Hypothesis 4:** In the presence of the FFM and cognitive ability, each EI stream exhibits incremental validity and relative importance in predicting job performance.

**Methods**

**Sample**

A number of search techniques were employed in order to maximize the likelihood of identifying empirical research related to EI and performance. We began by entering a variety of terms related to EI into electronic databases (e.g., ABI Inform, PsycInfo, and Google Scholar). We used EI and various
combinations of the following search terms: neuroticism, emotional stability, extraversion, openness, agreeableness, conscientiousness, GMA, cognitive ability, intelligence, job performance, sales, and supervisor rating. The combination of EI with these search terms identified over 900 citations. Additionally, a manual search of the most relevant journals (e.g., *Journal of Organizational Behavior, Journal of Applied Psychology, Leadership Quarterly, Academy of Management Journal, Journal of Management,* and *Personality and Individual Differences*) helped to identify articles that did not appear in the electronic searches. A legacy search, which involves “back tracking” an article by its references, helped to identify still more articles that could potentially be included in the study. The final search technique was to compare our results to those of prior EI meta-analyses (e.g., Van Rooy & Viswesvaran, 2004; Van Rooy, Viswesvaran, & Pluta, 2005; Joseph & Newman, 2010). The overlap was extensive; however, the previous meta-analyses did help to identify an additional 15 unpublished dissertations, working papers, and conference presentations. In sum, we identified 1163 citations relevant to the relation among EI, the FFM, cognitive ability, and job performance.

**Inclusion criteria**

We next created decision rules about which articles to include in the analysis. The first provision was that articles needed to be empirical and quantitative. We have no stipulations on date of publication, nationality of sample, or language. However, we did require either (1) a quantifiable performance outcome (e.g., supervisor rating, sales performance) or (2) a correlate to general intelligence/FFM (reported either in the article or by personal communication with the author). In operationalizing job performance we only included individual level performance outcomes and with the exception of three studies (Austin, Evans, Goldwater, & Potter, 2005; Carmeli, 2003; Wu & Stemler, 2008), all ratings were either objective or rated by a supervisor, peer, or subordinate. With regard to the three self-report performance ratings, all three studies used a stream 3 EI measure and to test if these studies skewed results, we ran the analyses with and without their inclusion. For both the overall analysis (EI and job performance) as well as the subset analyses (stream 3 EI and job performance) there were no changes in statistical significance nor did any effect size change more than 0.001.

In addition, some form of EI measure had to be included as a variable. The measure had to be explicitly designed to capture EI, so we did not include proxy measures (e.g., self-monitoring scales) in our meta-analysis. The EI variable could be dichotomous (e.g., low EI/high EI) or continuous (e.g., scale score). A final criterion was that each effect size needed to reflect a unique sample. That is, an article that used multiple measures of job performance on a single sample could only be entered into the database once. When authors did report multiple performance outcomes we averaged the correlates to obtain the effect size, a practice consistent with the guidelines provided by Hunter and Schmidt (2004), and corrected the variance of the averaged effect size using equations put forth by Borenstein, Hedges, Higgins, and Rothstein (2009). In the case where a study used multiple samples, each sample could be included as a separate entry as long as it met the other inclusion criteria. As explained above, we hypothesized that different streams of EI would vary in their relation to job performance and personality and individual differences. In order to test these hypotheses we coded the type of EI measure used (i.e., stream 1, 2, or 3), consistent with Ashkanasy and Daus (2005).

The final sample consisted of 43 effect sizes relating EI to job performance and between 67 (intelligence) and 80 (neuroticism) effect sizes for the individual difference correlates. Sample sizes ranged from 5795 for job performance to 17 088 for neuroticism. Table 1 gives the measures, type of research stream, and type of job performance examined.
Meta-analytic procedure

We employed a Hunter and Schmidt (2004) approach for this meta-analysis. We corrected for the reliability of EI and the outcome and present both corrected and raw correlations in the results. If an included study did not report the reliability, we used the average reliability of that particular scale or construct. The reliability of supervisor ratings are a particularly divisive issue in meta-analysis and 16 of the 43 studies used supervisor ratings to assess job performance. Of these 16 studies, eight reported the reliability (mean $\alpha = .80$). We used this value as the reliability for studies that did not report the reliability of job performance. Although the preponderance of included studies expressed the relation as a correlation, two studies did report group differences (i.e., high EI vs. low EI, both used a 50/50 split). In these instances, we first calculated the Cohen’s $d$ and then used Hunter and Schmidt’s (2004) $d$ to $r$ transformation equation.

Results

Overall results of the EI–job performance relation

Table 2 provides the results of the meta-analysis between EI and job performance as well as the relations between each EI stream and job performance. These data supported Hypothesis 1a indicating that the overall relation between EI and job performance is positive and significant ($r_c = 0.28$, $p < 0.001$). The percentage of variance attributable to sampling error is 47 per cent, a notable increase over the 27 per cent which Van Rooy and Viswesvaran (2004) reported. However, this percentage still falls short of the traditional Hunter and Schmidt (2004) criteria of 75 per cent which indicates the presence of potential moderators. However, in addition to the Hunter and Schmidt 75 per cent rule, we also examined the credibility intervals and found that they did not include zero, which indicates that the
EI streams and individual differences tests of heterogeneity

As Table 2 shows, the three streams of EI relate to job performance at similar levels and we found no significant differences between the streams \((Q(2, 42) = 1.44, p = ns)\). This indicates that all three streams of EI predict job performance at roughly equivalent levels and provides support for Hypothesis 1b. Although there were no significant differences between the EI streams in the prediction of job performance, this does not indicate that the three streams tap the same construct (presumably EI). The streams may have very different nomological networks. If the three streams truly measure the same EI construct, we would expect them to relate to other individual difference variables at similar levels.

EI and individual differences

Table 3 presents the results of each EI stream’s nomological network with regard to the FFM and cognitive ability. All three EI streams are positively related to extroversion, openness, agreeableness, conscientiousness, and cognitive ability, and negatively related to neuroticism. Thus, these data support Hypothesis 2. The small to moderate size of the correlations indicate that EI is related to these variables, as would be expected on theoretical grounds. Stream 3 has a corrected correlation of \(-0.54\) with neuroticism, and 0.49 with extroversion; all of the other corrected correlations are less than 0.40 in size. Although our studies for job performance only included working samples, we included student samples as well when examining the relationship between EI and personality. Consequently, we also tested whether student samples differed from working samples for this relationship. The results in the final column of Table 3 show that with one exception (out of 18 comparisons), EI relates to general intelligence and the FFM similarly for both students and workers.

Table 4 gives the tests for the differences between the three streams. For all six correlates (FFM and cognitive ability), we found significant \(Q\)-values indicating that the three streams relate to other personality and cognitive ability measures differently. Post hoc tests illustrated that stream 1 differed from stream 3 in all six cases, stream 2 differed from stream 3 for neuroticism and extraversion, and stream 1 differed from stream 2 for three of the FFM variables and for cognitive ability. These differences in how the EI streams related to other dispositional traits provide a contrasting perspective to the assertion that the various measures of EI assess the same construct.

Consistent with Hypotheses 3a and 3b, the ability measures of EI (e.g., MSCEIT) have the weakest relations with the FFM, but the strongest with cognitive ability. Also, consistent with predictions, the
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<th>Variable</th>
<th>$k$</th>
<th>$n$</th>
<th>$r$</th>
<th>$r_c$</th>
<th>Observed variance</th>
<th>Corrected variance</th>
<th>90% Credibility interval</th>
<th>95% Confidence interval</th>
<th>% of variance attributable to sampling error</th>
<th>Student vs. worker ($Q$)</th>
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<td>6829</td>
<td>−.471*'</td>
<td>−.544</td>
<td>.034</td>
<td>.043</td>
<td>−.760; −.182</td>
<td>−.534; −.408</td>
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<td>.024</td>
<td>.032</td>
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<td>.200; .331</td>
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<td>.018</td>
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<td>.006</td>
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<td>.027; .114</td>
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*p < 0.05, **p < 0.01.
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<th>Construct</th>
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<th>Stream 1–stream 2</th>
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<th>Stream 2–stream 3</th>
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<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>$Q(2, 80) = 62.49^{***}$</td>
<td>$Q(1, 47) = 15.82^{***}(2 &gt; )$</td>
<td>$Q(1, 55) = 60.99^{**}(3 &gt; )$</td>
<td>$Q(1, 55) = 17.51^{***}(3 &gt; )$</td>
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<tr>
<td>Extraversion</td>
<td>$Q(2, 79) = 56.57^{***}$</td>
<td>$Q(1, 46) = 16.98^{**}(2 &gt; )$</td>
<td>$Q(1, 58) = 54.45^{***}(3 &gt; )$</td>
<td>$Q(1, 54) = 6.04^{*}(3 &gt; )$</td>
</tr>
<tr>
<td>Openness</td>
<td>$Q(2, 71) = 12.77^{***}$</td>
<td>n/a</td>
<td>$Q(1, 50) = 12.73^{**}(3 &gt; )$</td>
<td>n/a</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>$Q(2, 71) = 8.24^{*}$</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>$Q(2, 74) = 50.39^{***}$</td>
<td>$Q(1, 43) = 29.51^{***}(2 &gt; )$</td>
<td>$Q(1, 52) = 47.85^{***}(3 &gt; )$</td>
<td>n/a</td>
</tr>
<tr>
<td>Cognitive ability</td>
<td>$Q(2, 77) = 28.25^{***}$</td>
<td>$Q(1, 47) = 17.68^{**}(1 &gt; )$</td>
<td>$Q(1, 63) = 25.63^{**}(1 &gt; )$</td>
<td>n/a</td>
</tr>
</tbody>
</table>

*p < 0.05. **p < 0.01. ***p < 0.001.
third EI stream that consists of expanded models of EI had the strongest relations with the FFM. Not surprisingly, the variance attributable to artifact was low for most of the FFM analyses. This certainly could be a result of some substantive moderator. However, the breadth of FFM measures introduces a sizable amount of variation (Morgeson et al., 2007) which likely attenuates this percentage.

**Incremental validity and dominance analysis of EI**

We propose that in determining whether a variable extends our understanding and prediction of job performance, it must account for variance beyond what is already accounted for by established predictors as well as demonstrate relative importance alongside these same established predictors. Thus, if EI fails to explain variance in the presence of cognitive ability and the FFM, and/or fails to demonstrate a significant level of importance relative to the other predictors, the ability of EI to contribute to the pursuit of explaining the ultimate criterion, job performance, in the fields of OBHRM is brought into question.

We, thus, tested the incremental validity of EI beyond the FFM and cognitive ability using criteria outlined in McDaniel, Hartman, Whetzel, and Grubb (2007). For the incremental validity tests, we used the observed correlations. In order to calculate the standard errors we followed guidelines put forth by Viswesvaran and Ones (1995) that call for the use of the harmonic mean as the sample size \((n = 68)\). The harmonic mean has come to be preferred above the arithmetic mean in meta-analytic management research (e.g., Colquitt, Conlon, Wesson, Porter, & Ng, 2001; Hirschcovis et al., 2007; Podsakoff, LePine, & LePine, 2007) because it gives less weight to extreme values and provides a more conservative approach to testing models (Colquitt, LePine, & Noe, 2000). Using these techniques, we were able to calculate the change in explained variance as well as the significance of the individual parameters.

**Construction of the correlation matrix**

To construct the correlation matrices for each EI stream we identified the most up-to-date and accurate correlations available. Along with the EI vector of effects drawn from the present work, we used meta-analytic true score estimates from four prior meta-analyses (i.e., Ackerman & Heggestad, 1997; Hurtz & Donovan, 2000; Mount et al., 2005; Schmidt et al., 2008). Specifically, Schmidt et al. (2008) provided the intercorrelations between conscientiousness, neuroticism, intelligence, and job performance. Because Schmidt et al. (2008) did not examine extraversion, agreeableness, and openness, we turned to Mount et al. (2005) for the remaining FFM intercorrelations, and Hurtz and Donovan (2000) provided these three FFM correlations to job performance. Finally, Ackerman and Heggestad (1997) provided the relations between intelligence and extraversion, agreeableness, and openness. Our guiding principle for selecting the correlations was to use the ones from the latest and most comprehensive meta-analyses available for each correlation. A correlation matrix of the FFM, cognitive ability, and job performance relations is presented in Table 5. The resulting correlations were inputted into an SPSS matrix regression macro developed by Johnson (2001).

**Limitations of meta-analytically derived correlation matrices**

When conducting any type of analysis with a meta-analytically derived correlation matrix, there are several important points to consider. First, the FFM and cognitive ability effect sizes from prior meta-analyses included different samples than those included in this meta-analysis. Therefore, it is possible that our samples vary in some important way from samples within prior meta-analyses and that this biases the results. Second, with regard to the job performance relations, the prior meta-analyses found evidence of, and corrected for, range restriction. Range restriction occurs when the distribution of
Scores between $X$ and $Y$ are truncated (Sackett & Yang, 2000). The result of range restriction is effect size attenuation. The key indicator for the presence of range restriction is if observed standard deviations are smaller than what is found in the population (a proxy of the population standard deviation is the standard deviation of the normative sample). We did not make this correction because we found no evidence of range restriction for EI. Third, the number of studies examining EI and job performance is significantly smaller than studies examining the FFM and job performance. Some researchers have argued that the common practice of attaching an FFM measure to studies even when there is no theoretical justification attenuates FFM effect sizes (e.g., Tett & Christiansen, 2007). Keeping these important notes in mind, we present the following dominance analysis. That being said, each correlation used here, whether identified in the present work or from another meta-analysis, is the best estimate of the true population effect – and, incremental validity tests as well as the use of epsilon weights reflects best practices in determining EI’s contribution to the study of job performance.

**Results of the incremental validity tests**

Table 6 presents the results of the analyses. Cognitive ability and the FFM combined to predict a substantial 42.3 per cent ($p < 0.001$) of the variance in job performance. Only cognitive ability and conscientiousness are significant predictors. The second column of Table 6 shows that the incremental contribution of stream 1 measures to the variance explained is minimal with an increase of only 0.4 per cent ($p = \text{ns}$). This is a modest increase when one considers that most stream 1 measures are lengthy and expensive. The contribution of streams 2 and 3 are substantially better. Stream 2 measures

---

**Table 5. Matrix of meta-analytically derived population estimates ($\rho$) used in dominance analysis**

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Neuroticism</td>
<td>-.13&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-.09&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Extraversion</td>
<td>.09&lt;sup&gt;c&lt;/sup&gt;</td>
<td>.08&lt;sup&gt;d&lt;/sup&gt;</td>
<td>-.24&lt;sup&gt;b&lt;/sup&gt;</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>5. Openness</td>
<td>.05&lt;sup&gt;c&lt;/sup&gt;</td>
<td>.33&lt;sup&gt;d&lt;/sup&gt;</td>
<td>-.19&lt;sup&gt;b&lt;/sup&gt;</td>
<td>.45&lt;sup&gt;b&lt;/sup&gt;</td>
<td>1.00</td>
<td></td>
<td></td>
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<tr>
<td>6. Agreeableness</td>
<td>.10&lt;sup&gt;c&lt;/sup&gt;</td>
<td>.01&lt;sup&gt;d&lt;/sup&gt;</td>
<td>-.42&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>.17&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>7. Conscientiousness</td>
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<td>-.04&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-.52&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>.09&lt;sup&gt;b&lt;/sup&gt;</td>
<td>.39&lt;sup&gt;b&lt;/sup&gt;</td>
<td>1.00</td>
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</table>

<sup>a</sup>Schmidt et al. (2008). <sup>b</sup>Mount et al. (2005). <sup>c</sup>Hurtz and Donovan (2000). <sup>d</sup>Ackerman and Heggestad (1997).

---

**Table 6. Results of incremental validity tests (harmonic mean of $n = 68$)**

<table>
<thead>
<tr>
<th></th>
<th>$\beta$</th>
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<th>$\beta$</th>
<th>SE</th>
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<td>.642**</td>
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<td>.659**</td>
<td>.099</td>
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<td>.100</td>
<td>.112</td>
<td>.070</td>
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<td>.116</td>
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<td>.104</td>
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</table>

$R^2 = .423^{**}$  $R^2 = .427^{**}$  $R^2 = .475^{**}$  $R^2 = .491^{**}$  $\Delta R^2 = .004$  $\Delta R^2 = .052^{*}$  $\Delta R^2 = .068^{-}$

<sup>a</sup>$p < 0.05$,  <sup>b</sup>$p < 0.01$. 

explained an additional 5.2 per cent of variance \((p < 0.05)\) beyond cognitive ability and the FFM and stream 3 explained an additional 6.8 per cent \((p < 0.01)\). The higher increment of stream 3 is not particularly surprising as composite measures are generally better predictors, but they do come at the cost of lower explanatory power (Jordan et al., 2010). In both models, the other significant predictors were cognitive ability, conscientiousness, and openness. Our results offered support to the incremental validity of streams 2 and 3, but called into question the incremental validity of stream 1. However, the abandonment of stream 1 measures of EI would be premature. The small change in variance accounted for would indicate that if cognitively ability and FFM data were already available then there would be minimum contribution of collecting a stream 1 EI measure. Certainly, this has some implications for the OBRHM literatures, but the incremental validity tests conducted with hierarchical regression do not speak to the relative contribution of EI. To fully test Hypothesis 4, we determined the relative weight of EI with dominance analysis.

**Dominance analysis of EI**

The hierarchical regression tests supported the inference that some EI streams provided incremental validity over the FFM and cognitive ability. However, the relative importance of EI is still unknown because beta weights can be compared in terms of rank-order, though their relative contribution to the total variance explained cannot (Johnson & LeBreton, 2004). To test Hypothesis 4, the relative importance of EI in the presence of the FFM and cognitive ability, we used relative importance analysis techniques outlined in Johnson (2000) and Johnson and LeBreton (2004).

**Review and rationale for epsilon weights**

Although the total predictive validity of a set of variables is of interest, most researchers often attempt to determine the importance of each predictor in a model as well. A variety of techniques exist to evaluate a predictor’s worth such as comparing beta weights or zero-order correlations, but these techniques are only valid when predictors are uncorrelated or when the interest is bivariate in nature. For instance, when comparing beta weights in a regression equation with correlated predictors there is a tendency for the good predictors to appear great and mediocre predictors to appear poor. Models with uncorrelated predictors are rare in OBHRM and most relations are multivariate in nature. Though popular, these techniques are inappropriate and provide misleading information when predictors are not orthogonal (Johnson & LeBreton, 2004).

The need for determining relative importance among a set of correlated predictors is perhaps greatest in meta-analysis – meta-analytic correlations are typically larger than observed correlations in primary data because of the various corrections for measurement error, publication bias, and range restriction commonly used in meta-analysis. The greater the intercorrelations among the predictors, the greater the multicollinearity, and the greater the need for dominance analysis. As meta-analyses become increasingly multivariate, researchers must incorporate different techniques to determine the relative importance of their predictors. Johnson’s (2000) epsilon weighting technique yields accurate estimates of the relative importance of a set of correlated predictors on an outcome. This technique was specifically designed for correlated predictors, can detect patterns of dominance (e.g., complete vs. conditional), and most notably, the estimates are intuitively meaningful in that they sum to the \(R^2\) and can be compared through ratios (Johnson & LeBreton, 2004). That is, an epsilon weight of 0.20 for a predictor is twice as important as another predictor in the model with an epsilon weight of 0.10 and the summation of the relative weights will be equal to the total variance explained.

---

1The authors are grateful to Michael Cole for this suggestion.
Relative importance

In order to test Hypothesis 4, which predicted that EI will demonstrate relative importance in the job performance models, it was necessary to operationalize relative importance. At present, there exist no formal standards of relative importance, but there are effect size standards put forth by Cohen (1988). \( R^2 \)-values of 0.01, 0.09, and 0.25 constitute small, medium, and large effects, respectively, and we used these thresholds to evaluate the magnitude of relative importance. It should be noted that Cohen (1988) set these standards for bivariate relations, not multivariate models as in the case with our dominance analyses. For instance, a medium effect at the bivariate level may become small or non-significant as other variables are added into a model. Therefore, Cohen (1988) standards can be viewed as considerably more conservative when applied to these dominance analyses with seven predictors (i.e., FFM, cognitive ability, and EI).

Results of the dominance analysis

The results of the relative dominance analyses for the three EI streams are shown in Table 7. For stream 1, 86.3 per cent of the total explained variance in job performance is attributable to cognitive ability and conscientiousness. Stream 1 contributes only 6.4 per cent of the explained variance and a small \( R^2 \) (0.03) contribution. Although minor, it does meet our threshold for a small effect, and so we conclude that stream 1 contributes relative importance compared to the FFM and cognitive ability.

For streams 2 and 3, results indicated that EI accounted for higher levels of variance. For stream 2, EI is second only to cognitive ability in terms of relative importance, capturing 13.6 per cent of the explained variance with an \( R^2 \) contribution of 0.065. Consequently, we concluded that EI stream 2 contributes a small to moderate amount of relative importance. The results were very similar for EI stream 3. This model, once again, is dominated by cognitive ability, but EI possessed a substantial relative importance percentage (13.2 per cent) and an \( R^2 \) contribution of 0.065. These findings offered support for Hypothesis 4. We concluded that all three EI streams, in varying magnitudes, contributed relative importance for predicting job performance.

Our results demonstrated that all EI streams, but most notably streams 2 and 3, provided additional explanatory power above and beyond the FFM and cognitive ability in the prediction of job

<table>
<thead>
<tr>
<th>Table 7. Relative importance of emotional intelligence</th>
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<td>-----------------------------------------------</td>
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<td>Neuroticism</td>
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</tr>
<tr>
<td>Openness</td>
</tr>
<tr>
<td>Agreeableness</td>
</tr>
<tr>
<td>Conscientiousness</td>
</tr>
<tr>
<td>Emotional intelligence</td>
</tr>
<tr>
<td>( R^2 = .427 )</td>
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</tbody>
</table>
performance. The use of epsilon weights in lieu of more common, but less accurate, methods allowed us to best demonstrate what role EI will play in the future of OBHRM. Overall, the present data did not offer support for claims that EI is the single most important predictor in job performance (e.g., Goleman, 1995). What we did find, however, are data which provided a contrasting perspective to the extant claims that EI is nothing more than cognitive ability and personality.

Publication bias

Considering our focus on providing accurate results from the relative importance analyses within the present research, it is useful to note that our findings are only as good as the studies used to derive these meta-analytic estimates. Therefore, it is important to ensure that the included studies are a fair representation of the population and not skewed by some systematic factor. One such systematic factor is publication bias.

A persistent concern in the literature is the effect of publication bias on meta-analytic results (Bösch, Steinkamp, & Boller, 2006; McDaniel, Rothstein, & Whetzel, 2006). Publication bias occurs when any systematic effort prevents a manuscript from being published based upon something other than the relevance and rigor of the study. Generally, publication bias occurs when a study’s findings are not statistically significant or the findings are contrary to accepted theory. The failure for studies with these types of findings to be published results in an inflation of the observed effect size (i.e., across a literature). For instance, if the consensus in the research community is that EI leads to higher job performance, then authors may find more difficulty publishing contradictory or null findings than those with positive results. This is especially so when the sample size that refutes the zeitgeist is small or the study is statistically underpowered in some other way.

Publication bias is examined by plotting the effect sizes observed in published studies on the X-axis and the precision (1/standard error) on the Y-axis and examining the distribution for asymmetry. Precision is roughly equivalent to sample size with higher precision values indicating less sampling error. We expected that if publication bias did exist, it would be to the lower left of the mean. This would indicate that studies which showed negative or null relations with job performance using smaller samples would be under-published. This would result in the meta-analytic results of the observed relations between EI and job performance being overestimated. When testing for publication bias, we only included published articles (i.e., we did not include dissertations, conference papers, or manuscripts in preparation).

The results of the publication bias tests are shown in Figure 1a–c. The white circles are the observed studies, the black circles are imputed studies based on Duval and Tweedie’s (2000) trim and fill technique. We used Comprehensive Meta-Analysis 2.0 (Borenstein, Hedges, Higgins, & Rothstein, 2005) to conduct the publication bias tests. The results of the publication tests indicate no, or minimal, bias for the EI streams. For stream 1 (k = 6) and 3 (k = 17), no evidence of bias exists to the left of the mean (see Figure 1a and c). For stream 2 (k = 6), we found small amounts of asymmetry indicating possible publication bias, but the two imputed studies needed to correct the asymmetry reduced the correlation by less than 0.04 (r_{observed} = 0.282, r_{adjusted} = 0.243) (see Figure 1b). At present, we find either no evidence, or very limited evidence, of publication bias in the EI and job performance literature. Although small or non-existent now, any construct that grows in prominence should expect increased likelihood of bias. As EI research continues to expand, great care should be taken to ensure fair representation of findings within future research.
Figure 1. Publication bias results: (a) stream 1 – no bias indicated; (b) stream 2 – two studies imputed; and (c) stream 3 – no bias indicated.
Discussion

We found that all three streams of EI correlated with job performance. Streams 2 and 3 incrementally predicted job performance over and above cognitive intelligence and the FFM. In addition, dominance analyses showed that when predicting job performance, all three streams of EI exhibited substantial relative importance in the presence of the FFM and intelligence. These findings offer insight into a number of important issues in the field. This work is the most comprehensive, and focused, EI meta-analysis to date including a substantially greater number of included studies than previous meta-analyses. Overall, we used the most current perspectives and accepted practices regarding meta-analyses and the present data strongly supported the predictive validity of EI in terms of job performance, above and beyond the FFM and cognitive ability.

Our findings also illustrated the similarities and differences in the nomological networks of the three EI streams. These differences have important implications in terms of the definitions and underlying constructs for the three streams of EI research. As expected, the stream 1 ability measures are more closely related to cognitive intelligence, and this supports the conceptualization of these measures as a type of intelligence test. The stream 1 measures also have the lowest correlations with the Big Five personality factors, again consistent with how these measures are conceptualized. The stream 1 measures significantly differ from the stream 3 measures for cognitive intelligence and all five personality measures, thus convincingly demonstrating that these are different measures. Since the stream 3 researchers now define their measures in terms of traits, competencies, and skills instead of intelligences, these results are again consistent with how these measures are defined. Stream 2 measures are significantly different from stream 3 measures for two personality traits, which support the conceptualization of stream 2 as distinct from stream 3 measures.

The finding that EI yields predictive validity above and beyond the FFM and cognitive ability is important for numerous reasons. First, these results support the work of several researchers who have argued that EI is an important predictor of work-related outcomes (Ashkanasy & Daus, 2005; Brackett & Mayer, 2003; Brackett et al., 2004; Daus & Ashkanasy, 2005; Dulewicz & Higgs, 2000; Dulewicz et al., 2003; Fox & Spector, 2000; Law et al., 2004). Second, our findings offer a contrasting perspective to the proposition that cognitive ability and the FFM account for enough variance in work-related outcomes that further research about relevant predictors is not useful. Specifically, our findings indicated that EI represents one important predictor of job performance – often considered the holy grail of outcomes in the OBHRM literatures.

Limitations and future directions

One limitation of this study, along with all meta-analyses, is that the number and type of moderators tested are limited to those reported in the literature. Importantly, for the present research, emerging literature related to EI focuses on the importance of contextual factors which may impact job performance (e.g., social interaction, levels of experienced stress on the job; Cherniss, 2010). We agree that these, and other, contextual factors exist and may impact the relation between job performance and EI. Jordan et al. (2010) highlighted the importance of context and raised questions related to when a low EI may be useful, or if some branches of EI may be helpful or harmful given different situations. These contextually oriented lines of inquiry are important to consider and, as the literature grows, we encourage future meta-analyses to include additional variables related to context.

Another limitation of the current research is that the measures we included for job performance were focused on task performance. Dalal (2005) demonstrated that job performance is actually composed of
three parts, each with a large impact on overall job performance. The facets of job performance not included in the present research were organizational citizenship behaviors and counterproductive workplace behaviors. Perhaps a more holistic view of job performance may result in even larger magnitudes between EI and performance. Future research may be well advised to explore these relations.

A final concern that is present in virtually all OBHRM studies with job performance as an outcome, and job performance meta-analyses in particular, is the issue of range restriction. Only a select number of individuals will be hired. Without information on those not selected for the job, the distribution is truncated and observed effect sizes are likely to be lower than population effect sizes. With this mind, one must concede that the correlations reported here, even those corrected for unreliability, are attenuated. Researchers still need to develop an estimate of the population standard deviation so that the methods of range restriction correction put forth by Gulliksen (1950) can finally be applied to EI.

In addition to the notes outlined above, there are numerous areas for future research that the present data illustrate. First, future research regarding the EI–job performance relation may have an impact in selection and hiring contexts. It is currently the case that EI is generally not used in personnel selection, while the FFM and cognitive ability are indeed used. This could affect the meta-analytically derived matrices, and we hope that the present research made a persuasive case for the inclusion of EI as well as the FFM and cognitive ability in applicable selection processes. Thus, future research would have the opportunity to build on the present findings and incorporate new, potentially compelling, data from an employee selection and hiring setting.

Second, future research might also examine the extent to which the relative importance of EI, cognitive intelligence, and personality varies by the type of job being performed. Although most jobs may involve at least some interpersonal contact relevant to EI, the degree to which jobs draw upon cognitive skills, various personality factors, and EI may vary considerably by job characteristics and other factors. In particular, researchers may want to focus on the contribution that EI plays in jobs requiring emotional labor and interactions with customers. Joseph and Newman (2010) have provided some preliminary evidence on this, but they also concluded that more research needs to be done on this topic. In particular, as Joseph and Newman (2010) pointed out, they only examined emotional labor in jobs that required the display of friendly, positive emotional displays to customers in retail and similar settings. According to Humphrey et al. (2008) typology of emotional labor, these customer “service with a smile” types of emotional labor are only one of three types of emotional labor performed by service workers: the other two are caring professions (e.g., health care, social work, childcare) and social control (e.g., policemen, bill collectors). Moreover, Humphrey et al. (2008) argued that leaders also perform emotional labor. Thus, the value of EI in these other job categories still needs to be studied. Along this line of thinking, researchers may also want to focus on how leaders can use their EI skills to influence the moods, motivations, and performance of their subordinates and team members. Furthermore, one final area of inquiry researchers may want to examine includes the different ways that educational and training programs can improve people’s EI-related abilities and skills.

**Conclusion**

The three streams of EI research, ability measures, self- and peer-report measures, and mixed models, all predict job performance equally well. Moreover, all three methods of measuring EI increment
cognitive ability and personality measures in the prediction of job performance. In this regard, we reach a somewhat different conclusion than Joseph and Newman (2010) who concluded that for overall job performance stream 1 measures added no incremental predictability above both cognitive ability and the Big Five personality factors. Although our tests for incremental validity also found that stream 1 measures did not increase the explained variance, our additional dominance analysis found that stream 1 measures accounted for 6.4 per cent of the explained variance – enough to make it the third most important predictor in the model. We also found a considerably higher incremental increase for stream 2 measures over and above cognitive ability and the Big Five (with a change in $R^2$ of 0.052 in our study, vs. 0.023 in Joseph & Newman, 2010). Joseph and Newman (2010) still found that stream 2 EI measures were the second most important predictor in their model (after cognitive ability), which is consistent with our dominance analysis. However, we have a lower estimate for the incremental increase due to stream 3 measures over and above both cognitive intelligence and the Big Five personality factors (our study, change in $R^2$ is 0.068; in their study, 0.142). Our dominance analysis revealed that stream 2 and 3 measures were roughly the same in the amount of the explained variance they accounted for (stream 2: 13.6 per cent; stream 3: 13.2 per cent).

Which EI method researchers and practitioners should pick depends on the purposes of the project, the feasibility of administering the tests or surveys, and similar factors. Stream 1 measures may be an excellent choice for selection and hiring. The objective nature of these tests may make them less susceptible to social desirability and faking effects. Because these measures do not require people to rate their own level of emotional competency, these measures may also be useful in giving feedback to participants and in helping people to understand their own current level of EI. Stream 1 measures may also be the best when scholars want to establish that there is an underlying ability called EI that meets traditional criteria for intelligence measures.

Stream 2 and 3 measures may be more feasible to use in many settings. Measures for streams 2 and 3 can easily be distributed as pen and paper surveys and they take relatively little time to administer. The survey format makes it easy to include other scales of interest to scholars and practitioners alike. The items can, without difficulty, be modified to focus on the particular work setting under investigation. Depending on the theory being tested, the ability to focus the items on how people are actually behaving in a setting may be theoretically preferable to stream 1 measures of ability. The added feasibility of stream 2 and 3 measures is not gained at the expense of predictive validity, as they increment predictions of job performance even better than stream 1 measures (i.e., this greater incremental predictability for streams 2 and 3 is most likely because they overlap less with cognitive ability, which is the best predictor of job performance).

Stream 2 measures have a lower correlation with cognitive ability than stream 1, and lower correlations with the FFM than stream 3. Thus, these measures are useful for establishing that EI is theoretically distinct from other related concepts. These measures may be an excellent choice for researchers who are concerned with differentiating EI from related variables while also increasing their ability to predict job performance. Finally, for those most interested in predicting job performance without concern for overlaps with other variables, the stream 3 measures have the greatest incremental predictive value. These measures may be of great use to practitioners or to theorists comfortable with a broad definition of emotional competencies.

Although many researchers take a single perspective that focuses exclusively on cognitive variables, or on the FFM, or on EI, the present research supports the conclusion that all three sets of variables predict job performance. Thus, moving forward, rather than seeing cognitive intelligence, the FFM, and EI as competing measures, researchers should focus on developing integrative models that include all three. This meta-analysis helps in this regard by showing the correlations among the three sets of variables. Understanding the relationships among these variables will be the first step in any integrative model.
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References

Articles marked with an asterisk are included in the meta-analysis.


EMOTIONAL INTELLIGENCE AND JOB PERFORMANCE


