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ORIGINAL PAPER

Cognitive Ability and Job Performance: Meta-analytic Evidence for the Validity of Narrow Cognitive Abilities

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Abstract

Cognitive ability is one of the best predictors of performance on the job and past research has seemingly converged on the idea that narrow cognitive abilities do not add incremental validity over general mental ability (GMA) for predicting job performance. In the present study, we propose that the reason for the lack of incremental validity in previous research is that the narrow cognitive abilities that have been assessed most frequently are also the abilities that are most highly correlated with GMA. Therefore, we expect that examining a broader range of narrow cognitive abilities that are less highly correlated with GMA will demonstrate incremental validity for narrow abilities. To examine this prediction, we conducted an updated meta-analysis of the relationship between cognitive ability and a multidimensional conceptualization of job performance (task performance, training performance, organizational citizenship behavior, counterproductive work behavior, withdrawal). Using several different methods of analyzing the data, results indicated that the narrow cognitive abilities that are the least highly correlated with GMA added substantial incremental validity for predicting task performance, training performance, and organizational citizenship behavior. These results have important implications for the assessment of cognitive ability and the employee selection process.

Keywords Cognitive ability · Employee selection · Job performance

One of the most widely accepted findings in organizational research is that cognitive ability predicts job performance, often substantially (Schmidt & Hunter, 1998; Schmitt, 2014). However, although the structure of cognitive ability is best described by both general and narrow cognitive abilities (Carroll, 1993; McGrew, 2009), it is the utility of general mental ability (GMA or *g*) that is typically emphasized (Ones et al., 2012; Schmidt, 2002). The consistent finding has been that GMA is the strongest predictor of job performance even when controlling for narrow cognitive abilities (i.e., GMA demonstrates incremental validity over narrow abilities). Consequently, it is a widely held belief, supported by a substantial body of research, that "not much more than *g*" is required for predicting job performance (Ree & Earles, 1991; Ree et al., 1994).

In this paper, we reevaluate the belief that "not much more than *g*" is important for predicting job performance. There are several reasons to suggest that such a reevaluation could be worthwhile. First, the practical value of cognitive ability for predicting workplace performance is, arguably, only likely to increase as the world of work becomes more complex and dynamic. As a result, if narrow cognitive abilities can add further utility/validity beyond GMA, then there exists untapped potential in our ability to understand and predict performance at work. Second, as we will discuss later in this paper, previous tests of the incremental validity hypothesis have been overly conservative in that they have focused primarily on the narrow abilities that are most highly correlated with GMA. The focus on GMA in our field has directed our collective efforts toward creating efficient measures of cognitive ability that primarily assess only those narrow abilities that are most strongly correlated with GMA (e.g., verbal and quantitative abilities). As a result, these high correlations limit the potential incremental validity of narrow cognitive abilities in the prediction of

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work outcomes. The third, and most important, reason to revisit the claim that "not much more than g" is important for predicting job performance is that research is starting to emerge that contradicts this claim and demonstrates the predictive validity of narrow cognitive abilities. Notably, a few studies have shown that narrow cognitive abilities can provide incremental validity over GMA under some conditions (Lang et al., 2010; Nye et al., 2020; Stanhope & Surface, 2014). Nevertheless, even these studies assessed only a limited range of narrow cognitive abilities, and these abilities were assessed using a single measure (Lang et al., 2010; Stanhope & Surface, 2014) or assessments that were confounded with other constructs (Nye et al., 2020).

In sum, although several studies have shown that "not much more than *g*" is important for predicting performance, recent research has begun to question the validity of this claim. As a result, there are a number of conflicting findings in this literature that necessitate further research. In addition, we believe that a comprehensive examination of this research question has yet to be conducted because a broad range of narrow abilities has not been simultaneously considered when examining the incremental validity of narrow abilities over GMA. Therefore, we suggest that the limited range of abilities that are typically assessed has hindered past research on this topic. Thus, the goal of the present study was to evaluate the relationships between GMA, narrow cognitive abilities, and job performance by conducting a meta-analysis that includes a comprehensive set of narrow abilities as well as multiple dimensions of job performance. The results of this study will help to clarify these relationships and provide additional information about how narrow cognitive abilities can contribute to the employee selection process.

The Structure of Cognitive Ability

To identify a definitive structure of cognitive ability, Carroll (1993) conducted a quantitative analysis of cognitive ability research. In his review of the literature, he identified 461 datasets that could be used to examine the factor structure of cognitive ability. Based on the results of factor analyses, Carroll proposed a hierarchical model of cognitive ability with a general ability factor (i.e., GMA) at the top, a set of narrower cognitive abilities in the second stratum of the model, and a broad range of specific factors underlying each of the narrow abilities. Importantly, Carroll found that some narrow abilities had stronger relationships with the general factor than others.

More recently, attempts have been made to integrate Carroll's (1993) model with similar models proposed by Cattell and Horn (Cattell, 1943, 1971; Horn & Blankson, 2005) due to the substantial overlap among the narrow abilities proposed in each of these models. One key difference between these models is that Carroll's model includes a GMA factor, but neither Cattell nor Horn proposed such a general factor. Thus, the integration effort has primarily focused on clarifying the narrow abilities (McGrew, 2009). To be specific, in addition to the narrow abilities included in Carroll's model, the models proposed by Cattell and Horn (a) included additional factors for quantitative knowledge and reading and writing, and (b) separated Carroll's memory factor into factors for short-term memory and long-term storage and retrieval. In short, the integrated model includes the hierarchical structure identified by Carroll (1993) and the additional narrow abilities suggested by Cattell and Horn. This integrated model is known as the Cattell-Horn-Carroll (CHC) model and is widely accepted as a comprehensive structure of cognitive ability (McGrew, 2009). Given the theoretical and empirical support for this model, we use this model as the underlying framework for the current study. Table 1 provides the definitions of the narrow abilities in this model.

The Validity and Incremental Validity of Narrow Cognitive Abilities

Numerous studies have examined the validity of GMA and narrow cognitive abilities for predicting work outcomes. This research has consistently supported the validity of GMA for predicting job performance (Schmitt, 2014) and selecting employees across a wide variety of jobs (Schmidt & Hunter, 1998). Debate still remains, however, about the value of narrow cognitive abilities for predicting work outcomes. For example, some of the most widely cited research on this topic has concluded that narrow cognitive abilities do not provide incremental validity over GMA for predicting either training or job performance (Ree & Earles, 1991; Ree, et al., 1994). Moreover, this finding occurs even when the content of the test is matched to the job (Murphy, 2009; Murphy et al., 2009). Based on these findings, several authors have concluded that the utility of cognitive ability for predicting job performance primarily lies with GMA and not with the narrow abilities (Ones et al., 2012; Ree & Carretta, 2002; Schmitt, 2014).

However, it is important to highlight that the bulk of the empirical evidence supporting the "not much more than g" position has been obtained in studies that assessed only a *limited* subset of the narrow abilities identified in the CHC model—typically, those that are most strongly correlated with GMA. To elaborate, although many earlier measures of cognitive ability assessed a broad range of narrow abilities (e.g., the General Aptitude Test Battery included psychomotor and auditory subtests), efforts to develop efficient measures of GMA have resulted in measures that only assess

Table 1 Definitions of narrow cognitive abilities in the Cattell-Horn-Carroll (CHC) integrated model

Narrow cognitive ability	Definition
Fluid Reasoning (*Gf*)	The use of deliberate and controlled mental operations to solve novel problems that cannot be performed automatically
Crystalized Intelligence (*Gc*)[a]	The knowledge of the culture that is incorporated by individuals through a process of acculturation. *Gc* is typically described as a person's breadth and depth of acquired knowledge of the language, information and concepts of a specific culture, and/or the application of this knowledge
General Knowledge (*Gkn*)	The breadth, depth and mastery of a person's acquired knowledge in specialized (demarcated) subject matter of discipline domains that typically do not represent the general universal experiences of individuals in a culture (*Gc*)
Visual Processing (*Gv*)	The ability to generate, store, retrieve, and transform visual images and sensations
Auditory Processing (*Ga*)	Abilities that depend on sound as input and on the functioning of our hearing apparatus. A key characteristic is the extent an individual can cognitively control (i.e. handle the competition between signal and noise) the perception of auditory information
Short-term Memory (*Gsm*)	The ability to apprehend and maintain awareness of a limited number of elements of information in the immediate situation
Long-term Memory (*Glr*)	The ability to store and consolidate new information in long-term memory and later fluently retrieve the stored information (e.g., concepts, ideas, items, names) through association
Processing Speed (*Gs*)	The ability to automatically and fluently perform relatively easy or over-learned elementary cognitive tasks, especially when high mental efficiency (i.e., attention and focused concentration) is required
Reaction and Decision Speed (*Gt*)	The ability to make elementary decisions and/or responses (simple reaction time) or one of several elementary decisions and/or responses (complex reaction time) at the onset of simple stimuli
Quantitative Knowledge (*Gq*)	The breadth and depth of a person's acquired store of declarative and procedural quantitative or numerical knowledge
Reading and Writing (*Grw*)	The breadth and depth of a person's acquired store of declarative and procedural reading and writing skills and knowledge

Definitions as provided by McGrew (2009, Table 1)

[a]Although this narrow ability is referred to as Comprehensive Knowledge in the CHC framework, we refer to it as Crystalized Intelligence in this study to be consistent with previous research and Carroll's (1993) terminology

a small number of narrow abilities that are highly correlated with GMA (Ackerman, 1996; Humphreys, 1994). For example, the ASVAB assesses verbal ability, quantitative knowledge, and spatial ability, all of which are highly correlated with GMA (Carroll, 1993; Lubinski, 2006). To illustrate this, Drasgow (2013) estimated a single factor model for the ASVAB subtests. In this model, all except two of the ASVAB subtests had factor loadings > 0.79 on the general factor. The two subtests that did not exhibit such high factor loadings have since been removed from the ASVAB, presumably to create an even more efficient measure of GMA and potentially at the expense of assessing narrow abilities. Using this updated version of the ASVAB, Brown et al. (2006), unsurprisingly, reported a lack of incremental validity for the narrow abilities over GMA when predicting training performance.

The fact that previous research has only examined a limited subset of narrow cognitive abilities is an important limitation that confounds the conclusion that "not much more than g" is important for predicting job performance. To clarify, the fact that many existing measures of cognitive ability assess relatively few narrow abilities that are highly correlated with each other limits the construct validity of these measures. Although the CHC model suggests that cognitive ability is comprised of both GMA *and* a number of narrow cognitive abilities (e.g., Carroll, 1993; McGrew, 2009), only a small subset of these narrow abilities are being assessed, meaning that the operationalization of the cognitive ability construct may be deficient in many modern measures (Ackerman, 1996; Humphreys, 1994). In addition, from a statistical perspective, additional predictor variables cannot account for substantially more variance in an outcome (i.e., increment validity) if these variables correlate highly with existing variables that are already in the model. Consequently, many of these previous studies (e.g., Ree & Earles, 1991; Ree et al., 1994) had severely limited potential for finding the incremental validity of narrow abilities over GMA because the narrow abilities assessed all tended to have strong correlations with GMA and each other. In other words, these measures of cognitive ability are not assessing the full domain of the construct and the narrow cognitive abilities that are being assessed are essentially providing redundant information due to their relatively high correlations.

Given the limitations of earlier studies on this topic, more recent research (Lang, et al., 2010; Mount et al., 2008; Nye et al., 2020; Stanhope & Surface, 2014) has started to examine the incremental validity of narrow abilities that are less highly correlated with GMA (e.g., processing speed, auditory processing, and visual processing; Carroll, 1993; McGrew, 2009). For example, Stanhope and Surface (2014) used the ASVAB to measure GMA and a separate test battery to assess a narrow ability known as audiolinguistic ability. They found that audiolinguistic ability demonstrated incremental validity over GMA for predicting training outcomes, whereas none of the narrow abilities measured by the ASVAB subtests did. Similarly, Lang et al. (2010) found the largest incremental validity for a subtest related to visual processing, while none of the other narrow abilities assessed in their study contributed substantially to the prediction of performance after controlling for GMA (i.e., $\Delta R^2 < 0.01$ for the other narrow abilities). Finally, a recent study by Nye et al. (2020) examined the prediction of training performance and found that a performance-based measure of narrow cognitive abilities like visual processing, auditory processing, and processing speed provided substantial incremental validity (i.e., ΔR^2 ranging from 0.08 to 0.10 across training criteria) over a separate measure of GMA. All of these studies provide initial evidence to support the claim (Krumm et al., 2014, p. 118) that there is greater potential for incremental validity when the narrow abilities that are assessed are less highly correlated with GMA. Therefore, we assert that examining a *broader* subset of the narrow cognitive abilities identified in the CHC model can provide a more comprehensive evaluation of their incremental validity over GMA.

Although the recent studies cited above call into question the claim that "not much more than g" is important for predicting performance, they also have several limitations that prevent definitive conclusions about the utility of narrow cognitive abilities from being drawn. For example, several of these studies only examined a limited subset of narrow cognitive abilities in the CHC model. The analyses by Lang et al. (2010) only examined a single measure of cognitive ability that had been used primarily in German samples. Therefore, the narrow cognitive abilities examined in that study were restricted to those assessed by that measure, which may not be representative of the broader CHC model. Similarly, Stanhope and Surface (2014) only examined the incremental validity of a single narrow cognitive ability. In both of these studies, only one narrow cognitive ability showed incremental validity over GMA but, again, this could be due to the limited number of narrow cognitive abilities that were assessed. In contrast, Nye et al. (2020) used a performance-based measure of cognitive ability that assessed several narrow cognitive abilities that are generally less highly correlated with GMA. However, the subscales of their performance-based measure assessed multiple narrow cognitive abilities simultaneously and were confounded with other factors inherent in the assessment method (e.g., psychomotor abilities). Therefore, their results could not be used to determine which narrow abilities were contributing to the overall prediction. In addition, all of these previous studies either examined training performance (Lang et al., 2010; Nye et al., 2020; Stanhope & Surface, 2014) and/or were limited to individual jobs (i.e., warehouse workers and Navy pilots; Mount et al., 2008; Nye et al., 2020). Therefore, although these recent studies provide compelling initial evidence for the incremental validity of narrow cognitive abilities, their results may not generalize to other samples, other dimensions of performance (e.g., task performance, OCB, or CWB), or even to the other narrow cognitive abilities that were not assessed. As a result, the existing evidence is not sufficient to fully contradict the research finding that "not much more than g" is important for predicting performance on the job.

In sum, there are conflicting findings in the literature about the incremental validity and relative importance of GMA and narrow cognitive abilities for predicting job performance criteria. Some studies have shown that narrow cognitive abilities provide only negligible incremental validity after controlling for GMA (Murphy, 2009; Murphy et al., 2009; Ree & Earles, 1991; Ree, et al., 1994) while others have found that adding narrow cognitive abilities to the model can significantly improve the prediction of training performance (Lang et al., 2010; Nye et al., 2020; Stanhope & Surface, 2014). Given the limitations of these previous studies, the debate continues and a more comprehensive evaluation of the incremental validity of narrow cognitive abilities is needed to resolve these discrepancies in the literature. Therefore, the present study attempted to address this issue by conducting a meta-analysis of the incremental validity of narrow cognitive abilities. Because both validity and incremental validity are likely to vary across narrow cognitive abilities, we examined the following research question:

> *Research Question 1*: Do narrow cognitive abilities add incremental validity over GMA for predicting job performance when a broader range of narrow abilities are examined?

Narrow Ability-Job Match

Recent work has suggested that the match between narrow cognitive abilities and work tasks will be particularly important for understanding the validity of narrow abilities (Krumm et al., 2014). When individuals have a high level of a particular narrow ability, logically, they should perform well on job-related tasks requiring that ability. For example, individuals with high quantitative ability should perform well in jobs (e.g., accounting) that require quantitative tasks. Research in the expert performance literature has provided indirect support for this effect by showing that expert levels of performance can be obtained through both ability and practice in a particular domain. In other words, high levels of performance are achieved when individuals with high ability in a particular area focus their time and effort on tasks related to that domain of performance (Hambrick et al., 2014).

Despite the intuitive appeal of this idea, other research has questioned the importance of the match between abilities and job tasks (Murphy, 2009). For example, Murphy et al. (2009) examined the effects of matching the content of a cognitive ability measure to the content of the job. They argued that the positive correlations among cognitive ability subtests would mitigate the effects of matching because individuals who do well on matched subtests would also tend to do well on subtests that do no match. They illustrated this effect by showing that different composites of ASVAB subscales can have very similar validities despite differences in their content. Given the debate surrounding the effects of matching narrow cognitive abilities to the tasks required on the job, we examined the following research question:

Research Question 2: Do narrow cognitive abilities have stronger validities for predicting job performance when the ability assessed matches the tasks required on the job?

Dimensions of Job Performance

Job performance is typically conceptualized as a multidimensional construct, with the most widely researched dimensions including task performance, training performance, organizational citizenship behavior (OCB), counterproductive work behavior (CWB), and withdrawal (Campbell, 2012). Despite the recognition that job performance is a multidimensional construct, much of the past research examining the relationship between cognitive ability and job performance—and especially between narrow cognitive abilities and job performance—has tended to focus on only the task or training performance dimensions. In part, this may be due to the expectation that the task and training dimensions of job performance are most strongly related to an employee's ability to learn new material. As Schmidt (2002) has noted, "general cognitive ability is essentially the ability to learn" (p. 188). Similarly, in Campbell's (2012) model of job performance, the effect of GMA on job performance was mediated through declarative and procedural knowledge. In other words, individuals scoring higher on GMA are able to obtain more declarative and procedural knowledge about their jobs that then leads to higher performance. Building on this work, research has shown that GMA is a much better predictor of task and training performance (Schmidt, 2002, 2014) when compared with other dimensions of job performance[1] (e.g., OCB [Gonzalez-Mulé et al., 2014], CWB [Dilchert et al., 2007], or withdrawal [Maltarich et al., 2010]; see also Borman & Motowidlo, 1997).

Although past research has found a stronger link between GMA and task or training performance, this research also suggests that there will be at least moderate relationships between cognitive ability and other specific dimensions of job performance, such as OCB or CWB. OCB is defined as a set of discretionary behaviors that are not explicitly recognized by the reward system of the organization but that still contributes to overall organizational performance (Organ et al., 2006). Gonzalez-Mulé et al. (2014) suggested that GMA may affect OCB through its effects on moral reasoning. These authors argued that higher GMA individuals have a greater capacity for moral reasoning (see also Jensen, 1998). As a result, individuals with high GMA will also have a better understanding of the moral reasons for engaging in OCB and the positive social consequences that can result. This suggests that GMA should be positively related with OCB.

In contrast, CWB is defined as any intentional employee behavior that is "viewed by the organizational as contrary to its legitimate interests" (Gruys & Sackett, 2003; p. 30). Dilchert et al. (2007) argued that GMA would have an inhibitory effect on CWB because individuals with high GMA are better able to learn and evaluate the potential consequences of their actions. Therefore, individuals with low GMA may be less able to accurately judge the negative implications of engaging in CWB. This would result in a negative correlation between GMA and CWB, which has been supported by previous research (Dilchert et al., 2007).

Similar to the relationship between GMA and CWB, there is also likely to be a negative relationship between GMA and withdrawal behavior. Withdrawal is typically defined as a set of behaviors that employees engage in to avoid or disengage from their work environment, tasks, or organization (e.g., absenteeism, lateness, withholding effort, turnover; Carpenter & Berry, 2017). From a conceptual standpoint, work withdrawal is often subsumed under the broader concept of CWB (Gruys & Sackett, 2003). In fact, in their meta-analytic review, Carpenter and Berry (2017) demonstrated that CWB and withdrawal are both conceptually and empirically related. Despite the overlap in these constructs,

[1] Here, we differentiate between overall job performance and specific dimensions of job performance. Overall job performance is the higher-order construct while the specific dimensions of job performance are the narrower forms of performance such as task performance, training performance, OCB, CWB, and withdrawal. In the present study, we focus on the specific dimensions of performance to examine differences in the prediction of these behaviors rather than the higher-order performance construct.

these authors also suggested that there may be differences in the underlying causes of these two outcomes. For example, CWB may be motivated by an intent to harm whereas withdrawal is characterized by an attempt to avoid specific work. Given these potential differences, we examined these behaviors separately in the current study. Nevertheless, due to the empirical overlap demonstrated by Carpenter and Berry (2017), we also expect GMA to be negatively related to withdrawal.

Although previous studies (e.g., Dilchert et al., 2007; Gonzalez-Mulé et al., 2014; Ree & Earles, 1991; Ree et al., 1994) have demonstrated that GMA is related to specific dimensions of job performance, it is important to recognize that most of these studies did not examine narrow cognitive abilities. Although some research has shown that narrow abilities *also* predict task and training performance (i.e., in addition to GMA; Lang et al., 2010; Nye et al., 2020; Stanhope & Surface, 2014), it is not currently known if narrow abilities predict task and training performance better than they predict other dimensions of job performance. Based on the assumption that narrow cognitive abilities also contribute to a person's capacity to learn domain-specific job-relevant material (e.g., reading and writing ability should predict learning the technical vocabulary required in a given job), we would expect narrow cognitive abilities to be better predictors of job performance dimensions that require learning (i.e., task and training performance) when compared with other dimensions where learning may be less relevant (e.g., OCB, CWB, and withdrawal). It seems plausible, however, that narrow cognitive abilities may also contribute to the prediction of other specific dimensions of job performance. As an example, being a subject matter expert in a particular domain (i.e., general knowledge, *Gkn*) may make it easier for a person, or make a person more willing, to help others or otherwise contribute to organizational goals (e.g., OCB). Thus, one contribution of the present study is to examine the relationships of both GMA and narrow cognitive abilities with five specific dimensions of job performance: task performance, training performance, organizational citizenship behavior (OCB), counterproductive work behavior (CWB), and withdrawal.

Hypothesis 1: (a) GMA will be better predictor of task and training performance than of OCB, CWB, and withdrawal; (b) Narrow cognitive abilities will be better predictors of task and training performance than of OCB, CWB, and withdrawal.

Although we expect both general and narrow cognitive abilities to predict similar job performance dimensions, it is less clear whether the *incremental* validity of narrow abilities will vary across these outcomes. To our knowledge, no previous study has examined this issue. Given the substantial role of GMA in learning, it is possible that narrow cognitive abilities may provide less incremental validity for predicting outcomes that require employees to learn new material than other outcomes such as OCB, CWB, and withdrawal. However, as suggested above, the extent of incremental validity should also depend on the magnitude of the relationships between GMA and narrow cognitive abilities. Nevertheless, we are not aware of any research that has examined this issue. Therefore, we also explore whether the incremental validity of narrow cognitive abilities varies across performance dimensions.

Research Question 3: Does the magnitude of incremental validity provided by narrow cognitive abilities over GMA vary across the specific dimensions of job performance?

Method

Literature Search and Inclusion Criteria

To identify studies for the present meta-analysis, we searched the following electronic databases for potentially relevant articles: American Psychological Association's PSYCINFO, ProQuest's Dissertation Abstracts, Business Science Premier, and the Institute of Education Sciences' Education Resources Information Center (ERIC). We conducted two separate searches in each of these databases. First, we searched for the following terms: *specific cognitive abilities*, *cognitive assessment*, *specific aptitudes*, *CHC theory*, *Cattell-Horn-Carroll theory*, *Gf-Gc theory*, *primary mental abilities*, *specific validity*, and *intelligence measures*. Second, we searched for each of the following terms *cognitive ability*, *intelligence*, and *mental ability*, in conjunction with the term *performance* (e.g., *cognitive ability* AND *performance*). We also reviewed the reference list of each relevant article for further citations that could be incorporated. Both published and unpublished studies were included in order to reduce the potential for publication bias.

To ensure that the results obtained from this meta-analysis would provide up-to-date information about the state of research on the validity of cognitive ability, we examined only those studies that had been conducted (i.e., the data were collected) within the last three decades (since 1990). In the present study, we use the CHC model as the organizing framework for the structure of cognitive ability. As noted by McGrew (2009), the first published measure that assessed many of the narrow cognitive abilities in the CHC model (though at the time it was only the Cattell-Horn model) was the Woodcock-Johnson test battery, which was published in 1989 (Woodcock & Johnson, 1989). Carroll's (1993) pioneering work on the structure of cognitive ability was then published in the early 1990s and the broader CHC model was proposed several years later (McGrew, 1997). Given that the CHC model provided a comprehensive structure of cognitive ability that clarified the content of many narrow cognitive abilities, we would expect that the studies conducted after the development of this model would use more uniform definitions and operationalizations of these narrow abilities. Therefore, focusing on articles published after the introduction of the Woodcock-Johnson test battery and subsequent refinements to the CHC model provides a useful evaluation of the modern conceptualization and measurement of cognitive ability. Our search identified over 3,000 articles that examined cognitive ability and performance and were published during this time frame.

Each article we identified was reviewed and included if it reported information about the correlation (or a statistic that could be converted into a correlation, e.g., t-statistic) between cognitive ability and job performance. Job performance was broadly defined to include task performance, training performance, OCB, CWB, and withdrawal. To be included in our review, a study also needed to: (a) use an adult sample; (b) include participants that were *not* selected based on cognitive or psychological disorders (e.g., we excluded studies that examined cognitive ability in participants with dementia or schizophrenia); (c) include participants who were current employees or prospective employees (e.g., trainees) and not undergraduate students; (d) examine a dimension of job performance rather than performance on a cognitive task; and (e) be written in English. While reviewing the set of included articles, we screened for whether a study used the same dataset as another study in our review. When multiple studies used the same dataset, information from the study with the largest sample size was retained. This was necessary given that several large-scale military datasets have been used frequently in this literature (e.g., Project A). Application of the inclusion criteria mentioned above resulted in 201 independent samples (from 164 unique studies) that reported a total of 896 correlations between cognitive ability and a specific dimension of job performance. A list of included articles can be found in the online supplemental material.

Coding of Studies

Type of Cognitive Ability

To code the type of cognitive ability that was measured, we created one dummy variable to reflect whether the correlation in a study was between job performance and GMA (coded 1), or between job performance and a narrow cognitive ability (coded 0). We created another 11 dummy variables to code for *which* of the narrow cognitive abilities in the CHC model (McGrew, 2009; see Table 1) was examined in a study. For example, if a study reported a correlation between fluid reasoning and a specific dimension of job performance, then the dummy variable for fluid reasoning was coded 1 and all the other dummy variables were coded 0.

Some articles reported correlations between job performance and both GMA and narrow abilities. If both GMA and narrow abilities were measured by the *same* assessment (i.e., GMA was computed as a composite of the narrow abilities), we included the correlations between job performance and narrow abilities and excluded the correlations between job performance and GMA. That is, if both GMA and narrow abilities were measured by the *same* assessment, we excluded the correlations between job performance and GMA to avoid including redundant information (i.e., GMA was just the sum of the narrow abilities and we use the narrow abilities to extract a latent factor for GMA below) and to meet the assumption of statistical independence among the observations. However, if GMA and narrow abilities were measured using *different* assessments, we included all of the correlations (i.e., correlations between job performance and narrow abilities as well as the correlations between job performance and GMA). Among the 896 correlations that were coded, 260 (29%) were correlations between GMA and job performance, and 636 (71%) were correlations between narrow cognitive abilities and job performance.

Specific Dimensions of Job Performance

In addition to coding each correlation in a study for the type of cognitive ability that was assessed, we also coded each correlation for the specific dimension of job performance that was measured. To that end, we created five dummy variables: *task performance, organizational citizenship behavior (OCB), counterproductive work behavior (CWB), training performance,* and *withdrawal*. Each dummy variable was coded 1 if the corresponding dimension of job performance was assessed and 0 otherwise.

Narrow Ability-Job Match

For the 636 correlations between narrow cognitive abilities and job performance, we attempted to code for the match between the narrow ability and the task demands of the job. To do so, we examined the original study for information about the job. If the results of a job analysis were provided, we compared the information reported by the authors with the narrow cognitive ability that was measured. If the narrow ability assessed matched a required knowledge, skill, ability (KSA) or task that was identified in the job analysis, the dummy variable was coded 1. Otherwise, it was coded 0.

Only a few of the articles in our database provided the necessary job analysis information to code for an ability-job match. For the rest of the articles, we used information provided on O*NET to code for the match between the narrow ability and the task demands of the job. Specifically, for each job/occupation, O*NET lists (and ranks by importance) the required tasks and KSAs for that occupation, as reported by subject matter experts. We used this information to identify the top three KSAs associated with each of the jobs included in our meta-analysis. If the narrow ability assessed in a study matched one of the top three KSAs identified for that job, the dummy variable was coded 1. Otherwise, it was coded 0.

Methodological Moderators

We also coded a number of methodological moderators for each study in our meta-analysis. First, because the validity of cognitive ability is larger when predicting objective rather than subjective measures of job performance (Schmidt, 2002), we coded each correlation in our database for whether the measure of job performance was objective or subjective. If the performance measure was based on objective criteria (e.g., number of customer complaints, volume of sales), the dummy variable was coded 1. Otherwise, if the performance measure was based on others' ratings (e.g., supervisory-rated task performance, coworker-rated OCB), the dummy variable was coded 0. Second, we coded for whether the study used a longitudinal or a cross-sectional design. If there was a time lag between the measurements of cognitive ability and job performance, a dummy variable reflecting study design was coded 1 (longitudinal). If cognitive ability and job performance were measured at the same time point, the study was coded 0 (cross-sectional). Finally, we also coded for the country that the data were collected in. Although the majority of the studies in our meta-analysis were conducted in the USA, a number of studies were also conducted in other countries. Therefore, we coded the country the data were collected in as an additional moderator in our study. If the data used for a study were collected in the USA, a dummy variable reflecting the origin of the sample was coded 0. Otherwise, if the data were collected in another country, this variable was coded 1. Studies that collected data from multiple countries or that did not report enough information to determine the country the data were collected in were excluded from these analyses.

Meta-analytic Corrections

The correlations reported in each primary study were corrected for both range restriction and unreliability in the performance measure. We did not correct for unreliability in the cognitive ability predictors; that is, we obtained operational correlations. Because some correlations were affected by direct range restriction (e.g., cognitive ability scores were used to select employees), whereas others were affected by indirect range restriction, we examined each study to determine the appropriate range restriction correction to apply. For example, if applicants were selected into the position based on cognitive ability scores (e.g., qualifying exam scores were used to screen out applicants), we applied corrections for direct range restriction. Otherwise, we corrected for indirect range restriction. Direct range restriction was observed most often for GMA while indirect range restriction was more common for narrow abilities. We used the methods proposed by Hunter et al. (2006) to perform all corrections.

To correct for range restriction, we used the sample (i.e., restricted) standard deviation (SD) for each cognitive ability score if it was reported in the original study. To obtain the unrestricted SD, we used the population estimate if it was reported in the original study. When these values were not reported, we searched for technical manuals for each of the cognitive ability measures in our analyses. If these manuals reported studies using a large number of participants to establish norms for the cognitive ability measure, we used the SDs from these norming samples as our estimates of the unrestricted SDs. When appropriate restricted or unrestricted SDs could not be identified, we used the average SD ratio (i.e., restricted SD/unrestricted SD) for cognitive ability measures across all studies to correct for range restriction. The average SD ratio across all studies was 0.89.

To correct for unreliability in the job performance measures, we used the reliability of the performance measure reported in the original study if it was available. When this value was not reported, we used reliability estimates obtained from meta-analyses. Specifically, we corrected subjective performance measures using a reliability estimate of 0.60 (Conway & Huffcutt, 1997) and we corrected objective performance measures using a reliability estimate of 0.61 (Sturman et al., 2005). For measures of performance that were unlikely to be affected by measurement error (e.g., administrative records of training grades or turnover), we assumed a reliability of 1.00.

Further, as noted by Hunter et al. (2006), corrections for indirect range restriction require that both the job performance measures and the cognitive ability measures be corrected for unreliability. Therefore, to correct for unreliability in the cognitive ability measures, we used the reliability estimate for the cognitive ability measure reported in the original study if it was available. When this value was not reported in the original study, we searched the technical manual for that cognitive ability measure (if available) to obtain a reliability estimate. If a reliability estimate could not be obtained from either of these sources, then we used the average reliability estimate (0.82) obtained across all the cognitive ability measures included in our database as our estimate. After correcting for indirect range restriction using the approach described by Hunter et al. (2006), we uncorrected the correlation for unreliability in the predictor

Table 2 Mean sample-size-weighted correlations among narrow abilities ($k=159$)

Cognitive ability	1	2	3	4	5	6	7	8	9	10	11	12
1. General Mental Ability (GMA)	–	0.68	0.67	0.50	0.50	0.35	0.50	0.48	0.49	0.61	0.85	0.75
2. Fluid Reasoning	0.72	–	0.46	0.30	0.34	0.22	0.35	0.67	0.33	0.22	0.41	0.43
3. Crystalized Intelligence	0.71	0.51	–		0.39	0.24	0.22	0.27	0.34	0.24		0.23
4. General Knowledge	0.52	0.37		–	0.15	0.05	0.10	0.08	0.17	0.13	0.55	0.54
5. Visual Processing	0.53	0.38	0.43	0.17	–	0.17	0.24	0.16	0.24	0.27	0.42	0.26
6. Auditory Processing	0.38	0.26	0.27	0.06	0.20	–	0.12		0.15	0.49		0.19
7. Short-term Memory	0.53	0.40	0.25	0.12	0.27	0.23	–	0.19	0.23	0.03	0.45	0.31
8. Long-term Memory	0.52	0.67	0.30	0.10	0.17		0.22	–	0.23			0.25
9. Processing Speed	0.53	0.38	0.39	0.20	0.28	0.17	0.27	0.26	–	0.12	0.44	0.24
10. Reaction and Decision Speed	0.64	0.25	0.28	0.13	0.31	0.53	0.04		0.15	–		0.17
11. Quantitative Knowledge	0.85	0.51		0.54	0.48		0.52		0.49		–	0.57
12. Reading and Writing	0.75	0.49	0.27	0.59	0.29	0.22	0.35	0.29	0.28	0.21	0.57	–

Corrected correlations are presented in the lower triangle; uncorrected correlations in the upper triangle

to obtain operational correlations. These operational correlations were then used for our meta-analyses.

Analytic Approach

Regression-Based Meta-analysis

We used a clustered regression-based approach to conduct the meta-analysis. In this approach, the dependent variable in the regression model is the effect size of interest (i.e., the correlation between cognitive ability and a specific dimension of job performance) and the predictor variables are the dummy codes for the potential moderators (e.g., type of cognitive ability, dimension of job performance). Thus, the regression intercept provides a baseline estimate of the relationship between cognitive ability and job performance when all the dummy variables are coded 0 and the regression slopes reflect the unique increment/decrement (from the baseline estimate) associated with each of the corresponding dummy variables.

One important feature of the regression-based approach is that it is able to handle multiple correlations from a single sample (e.g., correlations with different measures of GMA from the same sample), by properly accounting for the clustered (i.e., non-independent) nature of the effect size estimates included in our meta-analysis (Cochran, 1977). This was an important issue that needed to be dealt with, as many studies included in our review reported correlations between multiple measures of the same cognitive ability or the same dimension of performance. Although a common strategy to avoid violating the assumption of independence is to average across all of the correlations reported for the same sample to obtain a single effect size estimate for that sample (Hunter & Schmidt, 2004), this strategy limits the information used for the analyses and can affect the meta-analytic variance estimates and the ability to detect moderators (Gonzalez-Mulé & Aguinis, 2018). To ensure that we could include all of the correlations from every study, while accounting for the non-independence of these correlations, we used a regression approach to meta-analysis that has been used in previous research (e.g., Nye et al., 2017; Richman et al., 1999). This regression-based meta-analysis allowed us to test Hypothesis 1 and to address Research Question 2.

Incremental Validity Analyses

Although the regression-based meta-analysis provides bivariate validity estimates for GMA and narrow cognitive abilities, it does not provide a test of the incremental validity of narrow cognitive abilities over GMA. To examine incremental validity in addition to the bivariate validities, estimates of the intercorrelations among the narrow cognitive abilities are also required. Therefore, we conducted a separate meta-analysis to estimate these intercorrelations and the meta-analytic intercorrelation matrix is reported in Table 2.[2]

[2] To estimate the intercorrelations, we examined the correlation matrices provided in the original studies in our database. If at least two different cognitive abilities were measured in the same study, we coded the intercorrelations between those abilities when they were reported in the article. For studies that did not report these intercorrelations, we searched the technical manuals (if available) for the cognitive ability measure that was used and included the correlations reported in the manuals whenever possible. We identified 24 studies that reported correlations between two or more cognitive abilities. In addition, to supplement these 24 studies, we also included information reported by Carroll (1993), which is the most comprehensive and widely used study on the structure of cognitive ability to date. Carroll (1993) reported results from 135 additional samples that we used to calculate correlations between cognitive abilities. These correlations were then corrected for range restriction but not unreliability because we were interested in the operational validities. The procedures for correcting these correlations are described in the online supplemental material.

In this study, we used three different methods to examine incremental validity. First, consistent with previous research (e.g., Ree & Earles, 1991; Ree et al., 1994), we used hierarchical regression analyses. For these analyses, GMA was entered in Step 1 of the regression model, and the full set of narrow cognitive abilities was entered in Step 2. Incremental validity was determined by examining ΔR^2 in the model and the significance of the regression weight for each narrow ability (while controlling for GMA and all the other narrow abilities).

Second, we supplemented the hierarchical regression analysis with a relative weights analysis (RWA; Johnson, 2000) conducted using the RWeb statistical package (Tonidandel & LeBreton, 2015). Although hierarchical regression provides an estimate of the *unique* contribution that narrow abilities provide over GMA, some research has suggested that the use of hierarchical regression may help to explain the lack of incremental validity in past research on cognitive ability (Lang et al., 2010; Stanhope & Surface, 2014). This is because hierarchical regression is strongly affected by multicollinearity among the cognitive ability predictors. In contrast, RWA focuses on the *relative* contributions of GMA and narrow abilities to the prediction of job performance. To do this, RWA partitions the shared variance among *all* of the cognitive ability predictors to create orthogonal predictors. We note that this approach of partitioning the shared variance is inconsistent with the hierarchical CHC model. According to the CHC model, all the shared variance among the narrow abilities should be treated as an indication of GMA (Carroll, 1993; McGrew, 2009). Nonetheless, we conducted RWA to provide a point of comparison with previous research (Lang et al., 2010; Stanhope & Surface, 2014).

Finally, we also examined incremental validity using structural equations modeling (SEM). That is, to fully account for the shared variance among narrow abilities, we estimated a *latent* GMA factor by allowing all of the narrow abilities in the meta-analytically derived intercorrelation matrix to load onto a single latent factor. This one-factor model *is* consistent with the hierarchical CHC model, which represents GMA as a latent factor that describes the shared variance among the narrow abilities (Carroll, 1993; McGrew, 2009). We used this one-factor model and estimated paths from both the latent GMA factor and the observed scores for each of the narrow abilities to the specific dimensions of job performance.[3] For each of the three approaches used to examine incremental validity, separate models were estimated for each of the specific dimensions of job performance. In combination, these three different approaches to examining incremental validity (i.e., hierarchical regression, RWA, and SEM) allowed us to explore Research Questions 1 and 3.

[3] We could not estimate latent factors for the narrow abilities because we did not have item-level data in our meta-analytic database.

Table 3 Results of the meta-analytic regression model for cognitive ability

Variables	Model 1 β	Model 2 β
Intercept	.23*	.23*
Cognitive Ability Factor		
General Mental Ability (GMA)	.02	–
Fluid Reasoning	-.07	-.03
General Knowledge	.12	.09
Visual Processing	.07	–
Processing Speed	.10*	.15*
Quantitative Knowledge	.12*	.11*
Reading and Writing	.07	.06
Job Performance Dimension		
Task Performance	-.02	-.08
Training Performance	.10	.01
OCB	-.11*	-.23*
CWB	-.18*	-.20
Withdrawal	-.28*	-.23
Methodological Moderators		
Objective Measure of Performance	.14*	–
Longitudinal Study Design	-.11*	–
Sample Origin	-.05	–
Narrow Ability-Job Match	–	.02
$\boldsymbol{R^2}$	**.36**	**.23**

Model 1 is the original meta-analytic regression model that included all of the available studies in our database. In contrast, model 2 was estimated to test the effects of matching narrow cognitive abilities to the demands of the job (Research Question 2). GMA was excluded from model 2 because this general factor was not expected to depend on the match with any specific jobs

$^{*}p < .05$

Results

Meta-analytic Bivariate Validities of GMA and Narrow Abilities

The weights estimated in the meta-analytic regression model are shown in Table 3 and the meta-analytic estimates of the bivariate validities for GMA and narrow abilities estimated using these weights are shown in Table 4. As highlighted earlier, the dependent variable for the meta-analytic regression model is the corrected correlation between cognitive ability and job performance in each study and the predictors are the dummy codes for the potential moderators (e.g., type of cognitive ability, dimension of job performance,

Table 4 Meta-analytic corrected correlations between cognitive ability and performance

Variables	Task Performance		Training Performance		OCB		Withdrawal[b]		CWB[b]	
	Subj. Criteria	Obj. Criteria	Subj. Criteria	Obj. Criteria	Subj. Criteria	Obj. Criteria	Subj. Criteria	Obj. Criteria	Subj. Criteria	Obj. Criteria
Cognitive Ability Factor										
General Mental Ability (GMA)	.23	.37	.35	.49	.14	.28	.03	-.11	-.07	-.21
Fluid Reasoning	.14	.28	.26	.40	.05	.19	.12	-.02	.02	-.12
General Knowledge	.33	.37	.45	.59	.24	.38	-.07	-.21	-.17	-.31
Visual Processing	.28	.42	.40	.54	.19	.33	-.02	-.16	-.12	-.26
Processing Speed	.31	.45	.43	.57	.22	.36	-.05	-.19	-.15	-.29
Quantitative Knowledge	.33	.47	.45	.59	.24	.38	-.07	-.21	-.17	-.31
Reading and Writing	.28	.42	.40	.54	.19	.33	-.02	-.16	-.12	-.26
Other Narrow Abilities[a]	.21	.35	.33	.47	.12	.26	.05	-.09	-.05	-.19
Study Design										
Cross-Sectional Studies[a]	.21	.35	.33	.47	.12	.26	.05	-.09	-.05	-.19
Longitudinal Studies	.10	.24	.22	.36	.01	.15	.16	.02	.06	-.08
International Studies	.16	.30	.28	.42	.07	.21	.10	-.04	.00	-.14

OCB organizational citizenship behavior; *CWB* counterproductive work behavior. All values represent the estimated correlations corrected for range restriction and attenuation in the criterion

[a]Using the regression-based approach to meta-analysis, these correlations represent the baseline estimates of the meta-analytic correlations. As such, the baseline correlations represent the relationships between cognitive ability and performance in employed samples when the data are cross-sectional, collected in the USA, and subjective measures of performance (e.g., supervisory ratings) are used as the criteria

[b]The signs of the predicted correlations have been reversed back to their original direction. As such, negative correlations with cognitive ability indicate that individuals who score higher on cognitive ability will engage in less counterproductive work behavior and withdrawal

and methodological moderators). Therefore, the regression weights for this model (see Table 3) can be used to identify the most important factors for predicting variance in the correlation between cognitive ability and performance across studies. In addition, these weights can also be used to calculate the meta-analytic correlations represented in Table 4.[4]

The results presented in Table 4 provide the overall bivariate validities for both GMA and narrow cognitive abilities. One important finding was that the results were substantially different for subjective (e.g., supervisor ratings) and objective (e.g., volume of sales) performance outcomes. As shown in Table 4, correlations with objective criteria were larger than correlations with subjective criteria. For example, the meta-analytic correlation between GMA and task performance was substantially larger when task performance was operationalized using objective ($r_{corrected} = 0.37$), rather than subjective ($r_{corrected} = 0.23$) criteria. A similar pattern of results was also obtained for narrow abilities. For example, the meta-analytic correlation between visual processing and task performance was substantially larger when task performance was operationalized using objective ($r_{corrected} = 0.42$) rather than subjective ($r_{corrected} = 0.28$) criteria. Moreover, the significant regression weight shown in Table 3 for objective measures ($\beta = 0.14$, $p < 0.05$) indicates that the differences between these correlations are statistically significant. These results suggest that the objectivity of the criterion was an important moderator of the validity of both GMA and narrow cognitive abilities.

As shown in Table 4, and consistent with previous research, GMA was a strong predictor of several performance dimensions. Importantly, the results shown in Table 4 also indicate that narrow cognitive abilities have strong correlations with many of the performance outcomes. Although the CHC model describes 11 narrow abilities, our review of the literature only found correlations between job performance and six of these narrow abilities. This finding is consistent with the idea that relatively few narrow cognitive abilities are generally assessed and examined in the organizational literature. Thus, only the results associated with these six narrow abilities are shown in Tables 3 and 4. Nevertheless, the overall validity estimates for these narrow abilities were sometimes substantial. For example, the meta-analytic corrected correlations ranged from 0.28 to 0.47 for objective measures of task performance, from 0.40 to 0.59 for objective measures of training performance, and from 0.19 to 0.38 for objective measures of OCB. However, it is important to note that these are bivariate validities that do not demonstrate incremental validity over GMA (additional analyses to examine incremental validity are shown in the next section).

Finally, the results presented in Table 4 also indicate that longitudinal predictive designs generally resulted in smaller correlations than concurrent validity designs. Moreover, the significant regression weight presented in Table 3 (β = -0.11, $p < 0.05$) suggests that these differences were statistically significant. This finding is not surprising and suggests that validity may decrease when measurement of the predictor and the criterion are separated in time. This result is consistent with temporal models of the cognitive ability—performance relationship over time (Alvarez & Hulin, 1972). In contrast, the origin of the sample did not have a significant impact on the correlation between cognitive ability and performance (β = -0.05, $p > 0.05$).

Hypotheses 1a and 1b state that GMA and narrow cognitive abilities, respectively, will be better predictors of task and training performance than of OCB, CWB, or withdrawal. To test these hypotheses, the effect sizes of these differences are shown in Table 4. Consistent with Hypothesis 1a, GMA was more strongly correlated with task and training performance than with OCB, withdrawal, or CWB. For example, when job performance was measured using objective criteria, the correlations between GMA and task and training performance were 0.37 and 0.49, respectively. In contrast, the correlations between GMA and OCB, withdrawal, and CWB were 0.28, -0.11, and -0.21, respectively. Moreover, the regression results presented in Table 3 demonstrate that the correlations with OCB, withdrawal, and CWB were significantly *lower* than correlations with task and training performance, as indicated by the significant *negative* regression weights for these three performance dimensions (i.e., β = -0.11, -0.28, and -0.18, respectively, for OCB, withdrawal, and CWB).

The results reported in Table 4 for GMA are consistent with previous meta-analyses examining the validity of cognitive ability (e.g., Bertua et al., 2005; Hunter & Hunter, 1984; Salgado et al., 2003), although the magnitude of the correlations we obtained are slightly smaller than those reported previously. This is primarily due to the larger values used to correct for range restriction in the current study (i.e., average SD ratio = 0.89), as compared with the smaller values used in previous meta-analyses (average SD ratio = 0.65; Bertua et al., 2005; Hunter & Hunter, 1984; Salgado et al., 2003). The SD ratios used to correct for range restriction in the present study were estimated based on our meta-analytic database but would have resulted in smaller

[4] To calculate the meta-analytic correlations, the relevant regression weights for different conditions would simply be added to the intercept to estimate the overall effect size. For example, the meta-analytic estimate of the correlation between GMA and an objective measure of training performance is equal to .23 (intercept) + .02 (weight for GMA) + .10 (weight for training performance) + .14 (weight for objective performance) = .49 (see Table 4).

corrected correlations between GMA and performance than in previous studies, all else being equal.[5]

Consistent with Hypothesis 1b, narrow abilities also tended to be most strongly correlated with task and training performance and least strongly correlated with CWB and withdrawal. Again, correlations between the narrow cognitive abilities in our analyses and task performance ranged from 0.28 to 0.47 while correlations with training performance ranged from 0.40 to 0.59. In contrast, correlations with either withdrawal or CWB tended to range from 0.02 to 0.31 in absolute value. Interestingly, some narrow abilities appear to be as strongly correlated with OCB as with task and training performance. In fact, for OCB, many of the bivariate validities for the narrow cognitive abilities were greater than the bivariate validity for GMA.

Research Question 2 asks whether narrow cognitive abilities will have stronger validity for predicting job performance when the ability being assessed matches the tasks required on the job. To answer this research question, we ran a separate analysis to test whether the regression weight associated with the dummy variable for the narrow ability-job match contributed significantly to the meta-analytic regression model (see Table 3 Model 2). GMA was excluded from this model because it was not expected to depend on the match with any specific jobs—by definition GMA should relate to a broad range of tasks and jobs. We also excluded visual processing from these analyses because none of the studies that included visual processing in our review provided enough information to identify the match between this ability and job-related tasks. In other words, we estimated the narrow ability-job match based on five of the six narrow abilities included in our meta-analytic regression. Results indicated that the narrow ability-job match did not moderate the ability-performance relationship ($\beta = 0.02$, $p > 0.05$), suggesting that narrow abilities predict job performance across a broad range of jobs and not just in jobs that require that particular ability.

Incremental Validity of Narrow Cognitive Abilities over GMA

The results presented above indicate that both GMA *and* narrow cognitive abilities predict specific dimensions of job performance. Both GMA and narrow abilities demonstrated substantial validity for predicting task and training performance. In addition, when performance was measured objectively, both GMA and narrow abilities demonstrated moderate to large validities with OCB (Gignac & Szodorai, 2016). The question remains, however, as to whether narrow cognitive abilities add incremental validity over GMA for predicting job performance (Research Question 1). Addressing this question requires both the meta-analytic correlations between the cognitive ability predictors and job performance and the meta-analytic intercorrelations among the ability predictors (which we also estimated; see Table 2) to account for the relationships between GMA and narrow cognitive abilities.

Hierarchical Regression Analyses

For each job performance dimension, we estimated a separate hierarchical regression model to examine the incremental validity of narrow abilities (over GMA) for predicting that performance dimension. Each model was estimated based on: (a) the intercorrelations among the cognitive ability predictors, and (b) the correlations between the cognitive ability predictors and that performance dimension. Note that we re-estimated the meta-analytic correlations between the cognitive ability predictors and each performance dimension using a model that included only GMA, the narrow abilities, and the performance dimensions; that is, all other moderator variables were excluded from the regression model (cf. Tables 3 and 4). This was done so that the validity estimates would not be confounded with the levels of the moderator variables in the incremental validity analyses. Given that the correlations with both CWB and withdrawal were negligible for all of the cognitive abilities in our model (see Table 4), we did not examine incremental validity for predicting these specific dimensions of job performance.

For each hierarchical regression model, we added GMA as a predictor of performance in Step 1 and the narrow cognitive abilities in Step 2. The results of the hierarchical regression analyses are shown in Table 5 and indicate that narrow cognitive abilities added incremental validity for predicting all three performance criteria. When predicting task performance, the adjusted R^2 increased substantially after adding the narrow abilities to the model ($\Delta R^2 = 0.16$, $p < 0.05$). Similarly, when predicting training performance ($\Delta R^2 = 0.33$, $p < 0.05$) and OCB ($\Delta R^2 = 0.09$, $p < 0.05$), there were also moderate increases in prediction after adding the narrow cognitive abilities. Thus, in addressing Research Question 1, these results clearly show that narrow cognitive abilities add to the prediction of job performance outcomes, even after controlling for GMA.

Research Question 3 asks whether the incremental validity of narrow cognitive abilities *varies* across job

[5] To determine how much of an effect the smaller SD ratio had on the results of the present study, we re-ran our analyses using the smaller SD ratio to determine the meta-analytic correlation between GMA and performance. These exploratory results indicated that the meta-analytic correlation between GMA and task performance was .25 for subjective criteria and .40 for objective criteria. In addition, the meta-analytic correlation between GMA and training performance was .36 for subjective criteria and .51 for objective criteria. Despite these stronger correlations, we continue to use the SD ratio of .89 to correct for range restriction in all subsequent analyses because that correction corresponded to the data from the studies incorporated in this meta-analysis.

Table 5 Hierarchical regression results using the meta-analytic correlation matrix

Cognitive ability predictors	Task Performance	Training Performance	OCB
Step 1			
General Mental Ability (GMA)	.19*	.34*	.10*
Adjusted R^2	.04*	.12*	.01*
Step 2			
General Mental Ability (GMA)	-.77* (.00)	-1.08* (.01)	-.58* (-.01)
Fluid Reasoning	.07 (-.01)	.19* (.02)	-.01 (-.03)
General Knowledge	.18* (.09)	.26* (.12)	.14* (.07)
Visual Processing	.16* (.04)	.28* (.08)	.08* (.01)
Processing Speed	.27* (.08)	.40* (.11)	.20* (.05)
Quantitative Knowledge	.41* (.06)	.51* (.08)	.35* (.05)
Reading and Writing	.32* (.05)	.47* (.08)	.23* (.03)
Adjusted R^2	.20*	.45*	.10*
ΔR^2	.16*	.33*	.09*

*$p < .05$. The sample size for these analyses was 804, which is the average sample size across all correlations in the matrix. *OCB* organizational citizenship behavior. Values in parentheses represent the regression weights from the ridge regression model

performance criteria. As shown in Table 5, it does. The incremental validity over GMA was substantial when predicting both training performance ($\Delta R^2 = 0.33$, $p < 0.05$) and task performance ($\Delta R^2 = 0.16$, $p < 0.05$) but more modest, though still sizeable, when predicting OCB ($\Delta R^2 = 0.09$, $p < 0.05$).

As we noted earlier, the results of a hierarchical regression analysis are strongly affected by multicollinearity among its predictors. As seen in Table 2, GMA correlates substantially with several of the narrow abilities (e.g., 0.72 with fluid reasoning, 0.85 with quantitative knowledge, and 0.75 with reading and writing). These substantial correlations could help to explain why adding narrow abilities in the hierarchical regression models (shown in Table 5) resulted in the positive regression weights for GMA becoming negative. To help account for multicollinearity among the cognitive ability predictors, we used ridge regression (Hoerl & Kennard, 1970) and again estimated separate models for each job performance dimension. The results of the ridge regression models are shown in parentheses in Table 5. After accounting for multicollinearity: (a) the negative regression weights for GMA were reduced to nearly zero, (b) the regression weights for the narrow abilities that were the most highly correlated with GMA (e.g., fluid reasoning, reading and writing) were also reduced, and (c) the regression weights for the narrow abilities that were less highly correlated with GMA (e.g., general knowledge, visual processing, and processing speed) remained strong predictors of performance.

In short, these results provide further evidence that narrow cognitive abilities add to the prediction of job performance, even after accounting for GMA. Narrow abilities that were less highly correlated with GMA tended to provide the strongest additional prediction of performance. Similarly, narrow abilities also predicted performance when multicollinearity among the predictors was taken into account.

Relative Weights Analysis (RWA)

To further supplement the hierarchical regression analyses, we also conducted RWA. The results of these analyses are presented in Table 6. First, consistent with the results of the hierarchical regression analyses, RWA indicated that narrow abilities contributed substantially to the prediction of task performance, training performance, and OCB. For example, results indicated that GMA explained approximately 10% of the variance that was explained when predicting each of these job performance dimensions (i.e., 10.49% of the variance accounted for when predicting task performance, 9.16% of the variance accounted for when predicting training performance, and 12.32% of the variance accounted for

Table 6 Rescaled results of the relative weights analysis

Cognitive ability predictors	Task performance	Training performance	OCB
General Mental Ability (GMA)	10.49	9.16	12.32
Fluid Reasoning	2.58	4.12	4.49
General Knowledge	24.26	22.45	24.58
Visual Processing	7.52	11.65	3.79
Processing Speed	22.33	22.55	20.41
Quantitative Knowledge	18.31	15.19	21.21
Reading and Writing	14.50	14.88	13.20
R^2	**.21**	**.46**	**.11**

Values in this table are the rescaled relative weights, which represent the percentage of predicted variance accounted for when predicting OCB). In contrast, the narrow cognitive abilities in the model explained approximately 90 percent of the remaining variance accounted for in each of these performance dimensions.

Second, consistent with the results from the ridge regression models, RWA clarified the importance of general knowledge and processing speed for the prediction of task performance, training performance, and OCB. Specifically, these narrow abilities—which had some of the lowest correlations with GMA—accounted for the highest proportion of the total variance accounted for in these performance outcomes. Both of our attempts to address the issue of multicollinearity (using ridge regression and RWA) thus suggest a consistent result: narrow abilities that are less strongly correlated with GMA (e.g., general knowledge and processing speed) are likely to provide better incremental validity than narrow abilities that are more strongly correlated with GMA (e.g., quantitative knowledge and reading and writing). This conclusion differs from the conclusion drawn by focusing solely on the hierarchical regression analysis, which showed that narrow abilities that are more strongly correlated with GMA (e.g., quantitative knowledge and reading and writing) had larger regression weights. Our supplemental analyses thus clarify that these hierarchical regression results were at least partially due to the effects of multicollinearity and provide guidance as to *which* narrow cognitive abilities might provide incremental validity over GMA.

Structural Equation Modeling

Although the results presented in Tables 5 and 6 suggest that narrow cognitive abilities can add incremental validity over GMA, these results may not fully account for the relationships between GMA and the narrow abilities. The CHC model represents GMA as a latent factor that accounts for the shared variance among the narrow cognitive abilities (Carroll, 1993; McGrew, 2009). In contrast, the relationships between the general and narrow cognitive abilities that were used for the incremental validity analyses presented above were taken from previous studies that reported results from separate measures of GMA and narrow abilities. Using a separate measure of GMA, rather than estimating it as the shared variance among the narrow abilities (i.e., as in the CHC model), could result in GMA scores that are a combination of both the shared variance and the aggregated unique variance attributable to each narrow ability. Therefore, it is possible that the results would differ if we estimated a general factor based on the correlations among the narrow abilities. To address this issue, we next used structural equations modeling (SEM) to examine the incremental validity of narrow abilities over the general factor.

Using the corrected correlations shown in Table 2, the initial one-factor model did not fit the data well (RMSEA = 0.16, CFI = 0.89, TLI = 0.81, SRMR = 0.06). Further analysis of this model indicated that quantitative knowledge, reading and writing, and general knowledge were still highly correlated even after accounting for the general factor. This is consistent with Carroll's (1993) model, which combined these three narrow abilities into crystalized intelligence. Therefore, we estimated an additional model with correlated errors[6] between general knowledge and both quantitative knowledge and reading and writing. The resulting model fit the data substantially better (RMSEA = 0.10, CFI = 0.96, TLI = 0.92, SRMR = 0.04) and the factor loadings for this model are shown in Table 7. Consistent with the CHC model, fluid reasoning, quantitative knowledge, and reading and writing ability had the strongest loadings on the general factor. In contrast, general knowledge had the lowest factor loading.

Table 7 Factor loadings on the general mental ability (GMA) latent factor

Narrow cognitive abilities	Factor loadings
Fluid Reasoning	.63
General Knowledge	.46
Visual Processing	.55
Processing Speed	.55
Quantitative Knowledge	.86
Reading and Writing	.65

The sample size for these analyses was 804, which is the average sample size across all correlations in the matrix

Next, we used this one-factor model to estimate the validity of both general and narrow cognitive abilities. To do so, we included paths from both the general factor estimated in the factor analytic model and each of the narrow cognitive abilities to job performance. Separate models were estimated for each job performance dimension: task performance, training performance, and OCB. The results of these models are shown in Table 8. In these models, the narrow cognitive abilities added incremental validity for predicting all three job performance dimensions. The largest path coefficients were observed from the narrow cognitive abilities with the weakest relationships to GMA. General knowledge, visual processing, and processing speed all had the smallest loadings on the general factor (see Table 7) but had the largest effects on each of the performance outcomes. Both general knowledge and processing speed had the strongest positive relationships with all three performance dimensions. Visual

[6] Although estimating a latent factor using these three narrow abilities may be methodologically preferable to correlating errors, we used correlated errors so that we could examine the incremental validity of quantitative knowledge, reading and writing, and general knowledge separately in this model.

Table 8 Results of the SEM analyses of the meta-analytic correlation matrix

Cognitive ability factors	Task performance	Training performance	OCB
GMA (Latent Factor)	.07	.06	.04
Fluid Reasoning	-.15	-.11	-.20*
General Knowledge	.24*	.33*	.19*
Visual Processing	.08	.17*	.11
Processing Speed	.19*	.28*	.14
Quantitative Knowledge	.01	-.02	.01
Reading and Writing	.04	.09	.02
R^2	.17*	.37*	.10*

*$p < .05$. $N = 804$. *GMA* general mental ability

processing was only a significant predictor of training performance, but also had relatively strong path coefficients to both task performance and OCB.

In most cases, the narrow abilities that had the strongest loadings on the general factor (i.e., fluid reasoning, quantitative knowledge, reading and writing) also had small and nonsignificant relationships with each of the performance outcomes after controlling for the general factor. In fact, the weights for fluid reasoning were negative for all three outcomes. However, as with the regression analyses presented above, these negative path coefficients are likely due to multicollinearity between this narrow ability and the latent GMA factor.

Discussion

The goal of the present study was to examine the relative contributions of GMA and narrow cognitive abilities to the prediction of job performance. Consistent with previous research, we found that GMA is strongly related to multiple dimensions of job performance. We also demonstrated that the magnitudes of these correlations varied substantially across criteria. Specifically, we found strong correlations with task and training performance, moderate correlations with OCB and objectively reported CWB, and smaller correlations with withdrawal. To our knowledge, this is the first study that has simultaneously compared the validity of GMA across all of these dimensions of job performance. Nevertheless, this general pattern of results is consistent with previous research examining the relationships between GMA and each of these outcomes in separate studies (Dilchert et al., 2007; Gonzalez-Mulé et al., 2014; Maltarich et al., 2010; Schmidt & Hunter, 1998).

Although the general conclusions about GMA replicate previous research, the magnitudes of the relationships found in the present study are slightly smaller than in previous studies. There are many potential explanations for these slightly smaller correlations. First, the present study summarizes the most recent data on the relationship between cognitive ability and performance. Second, as described above (see footnote #5), the present study used a larger correction factor than incorporated in previous research, resulting in smaller corrected correlations. However, this larger correction factor was based on the observed data and, therefore, was more appropriate for the current study. Despite the relatively lower correlations found in the present study, the overall conclusion is still the same—GMA is a strong predictor of job performance.

In addition to the substantial correlations with GMA, we also found that *narrow* cognitive abilities demonstrated moderate to large validities for predicting multiple dimensions of job performance. This result extends previous research by examining a broader range of narrow abilities, multiple measures of cognitive ability, and multiple dimensions of job performance. Crucially, our meta-analysis indicates that narrow cognitive abilities show incremental validity over GMA for predicting task performance, training performance, and OCB. Moreover, these results were obtained across three different analytic methods (i.e., hierarchical regression analyses, relative weights analyses, and SEM). This finding contradicts the generally held belief that "not much more than *g*" is important for predicting either task performance (Ree et al., 1994) or training performance (Ree & Earles, 1991) and demonstrates that narrow abilities predict specific dimensions of job performance even after controlling for GMA.

Further, we found that the narrow abilities that are the least strongly correlated with GMA (e.g., visual processing, general knowledge, processing speed) provided the greatest increments to validity. This is of particular relevance because the influential research showing that "not much more than *g*" is required for predicting performance (Ree & Earles, 1991; Ree et al., 1994) used the ASVAB to operationalize both GMA and narrow cognitive abilities. However, the narrow abilities assessed by the ASVAB (e.g., reading and writing, quantitative knowledge) are highly correlated with each other and with GMA (Drasgow, 2013), which limits their potential for incremental validity. Thus, our results suggest that past research on the incremental validity of narrow abilities may have been limited by the specific types of narrow abilities that were assessed (Humphreys, 1994; Mount et al., 2008).

It is worth noting that the relationship between GMA and performance decreased substantially after controlling for the full range of narrow cognitive abilities. As described above, the low and sometimes negative relationships between GMA and specific performance dimensions were at least partially due to multicollinearity. Nevertheless, even after controlling for multicollinearity, the relationships between performance and GMA remained low. This is most likely due to the inclusion of a more comprehensive set of narrow cognitive abilities in the model. Because GMA is a broader construct that reflects the shared variance among all narrow abilities , examining a limited number of narrow abilities, as was done in many previous studies, means that the general factor could account for additional variance that is associated with both the unmeasured narrow abilities and the outcome. In contrast, in the present study, where we included a more comprehensive set of narrow abilities, there was less unique variance associated with GMA to increase the prediction of performance. This was particularly true in the SEM analyses where GMA was estimated as a latent factor and added little to the prediction of performance after controlling for narrow abilities. As an example, when only the relationship between GMA and training performance was estimated (i.e., none of the relationships between training performance and narrow abilities were controlled), the path estimate was 0.57. However, after controlling for the relationships with narrow abilities, the relationship between GMA and training performance decreased to 0.07. This again suggests that a more comprehensive set of narrow abilities should be measured in future research.

Another potential explanation for the different incremental validity findings in previous research is the way that the general factor was operationalized. In some of the most widely cited studies showing that narrow cognitive abilities do not add incremental validity over the general factor (Ree & Earles, 1991; Ree et al., 1994), the general factor was operationalized as the first principal component in a principal components analysis (PCA) and narrow cognitive abilities were operationalized as the remaining unrotated principal components in the model. Although PCA is a useful method for data reduction, it does not estimate the general factor hypothesized in the CHC model (Jackson et al., 2015)—i.e., a common factor that represents the shared variance among several narrow cognitive abilities. To elaborate, PCA does not differentiate between the shared variance among the narrow abilities (attributable to GMA) and the unique variance attributable to each narrow ability (Fabrigar et al., 1999; Jackson et al., 2015). This is because PCA estimates a set of linear composites comprised of the narrow cognitive abilities and containing both their shared variance and their unique variance. Therefore, using the first principal component to operationalize GMA attributes potentially meaningful variance that should be attributed to each narrow ability to the general factor. In contrast, the CFA/SEM approach used here and summarized in Tables 7 and 8 separates the shared variance among the narrow cognitive abilities from the unique variance and provides a more realistic estimate of the incremental validity of narrow cognitive abilities.

One important advantage of the present study was the use of meta-analytic regression (Gonzalez-Mulé & Aguinis, 2018). This approach incorporates all of the available information from the studies included in the meta-analysis and, therefore, provides more accurate estimates of the standard errors (Nye et al., 2017). This approach also allowed us to examine the combined effects of several moderators (e.g., objective vs. subjective performance), instead of the effect of each moderator in isolation. By examining a moderation effect in conjunction with other moderating effects, we improved upon previous meta-analytic studies that often rely on the untenable assumption that the presence of one moderator is "unaffected by the presence of other boundary conditions" (p. 2248; Gonzalez-Mulé & Aguinis, 2018).

Finally, the meta-analytic regression approach also has greater power to detect statistically significant moderation effects because it is relies on the total number of effect sizes available for analyses rather than the number of studies contributing to a specific effect (i.e., k). Therefore, although *the number of studies reporting a specific effect* might be small, the meta-analytic regression approach will still have sufficient power to detect these moderation effects and estimate the meta-analytic effect size. This is particularly relevant for the present study in which k varies substantially across the narrow cognitive abilities examined. For example, although $k=40$ for quantitative ability (156 correlations), k was only 15 for processing speed. However, there were 43 correlations reported across the 15 studies that examined processing speed. Given this variability, the meta-analytic regression approach provides important advantages for examining the correlation differences across narrow cognitive abilities. Nevertheless, the accuracy of the regression model will continue to improve as the number of data points increases. Therefore, future research should continue to replicate these effects and provide updated estimates of the relationships between various narrow cognitive abilities and specific dimensions of job performance.

Implications for Theory and Research

Our findings advance understanding of how narrow cognitive abilities relate to job performance in several ways. First, past research has strongly emphasized the importance of GMA for the employee selection process (Ones et al., 2012; Ree & Carretta, 2002; Schmidt & Hunter, 1998), and correspondingly, placed far less emphasis on the importance of narrow abilities when selecting job applicants. The results of the present study, however, suggest that narrow cognitive abilities improve the prediction of job relevant outcomes and, therefore, may add utility to the selection process. In particular, narrow cognitive abilities that are the least highly correlated with GMA, such as general knowledge, processing speed, and visual processing, had the largest effects on performance even after accounting for GMA.

Second, our results suggested that the match between the narrow ability and job tasks did *not* have a substantial effect on the relationships between cognitive ability and performance. One possible explanation for these findings is that the *breadth* of each of the specific job performance dimensions assessed (e.g., task performance or organizational citizenship behavior) was incompatible with the narrower cognitive abilities. If the primary studies in our review had included narrower dimensions of job performance, such as performance on quantitative tasks, the findings might have been different. This explanation is consistent with the compatibility principle proposed by Schneider and Newman (2015). Unfortunately, we could not find a sufficient number of studies that reported relationships between narrow cognitive abilities and narrow job performance dimensions in the context of the present study.

Interestingly, the results of our meta-analysis also indicate that the validities of both GMA and narrow abilities were significantly higher when performance was measured objectively. Although this finding is consistent with previous research on cognitive ability (Hunter, 1986; Schmidt, 2002), it is unclear why this might be the case. Past research has demonstrated that objective and subjective performance measures are not interchangeable (Bommer et al., 1995). The reasons for this lack of consistency between objective and subjective performance appear to be a combination of both rater effects and the situational constraints associated with subjective ratings (Murphy, 2008). From this perspective, future research and practice may benefit from focusing on predicting objective measures of performance. However, objective measures of performance also have limitations in that they are contaminated by situational constraints on performance. In addition, one difficulty with attributing these differences to the limitations of subjective performance ratings is that previous research has failed to find similar differences when examining non-cognitive predictors such as personality (Tett et al., 1991) or vocational interests (Nye et al., 2017). As such, there appears to be an important distinction between the prediction of subjective and objective performance, but only when considering cognitive ability. Therefore, future research should examine the relationships between cognitive ability, subjective performance ratings, and objective measures of performance to help identify these differences.

Finally, another potential direction for future research is to examine the mechanisms for the relationships between narrow cognitive abilities and performance. Past research has suggested that the relationship between GMA and performance is mediated through job knowledge (Campbell, 2012; Schmidt et al., 1986). In other words, people with higher levels of intelligence are able to learn more (or learn more quickly) job-relevant knowledge than others, which will help to facilitate performance. Therefore, it would be useful to examine whether similar mechanisms apply to narrow cognitive abilities. This seems likely given that many of the narrow abilities that added the most incremental validity in the present study can also facilitate learning. For example, visual processing and processing speed, which both added incremental validity over GMA in the present study, can help employees to gather information (i.e., visual processing) and process that information more quickly (i.e., processing speed). Therefore, these narrow abilities may facilitate learning on the job.

In the present study, general knowledge also added incremental validity over GMA. As general knowledge represents the sum total of *existing* knowledge that a person has obtained over time (i.e., knowledge a person already has), the relationship between this narrow ability and learning is complicated. This is because the knowledge a person possesses could be directly related to the job (e.g., an accountant who knows a lot about math), indirectly related to the job (e.g., a salesperson who knows a foreign language that helps to improve communication with customers who speak that language), or completely irrelevant to the job (e.g., a mechanic who knows a lot about geography). Consequently, it is unclear whether general knowledge is related to performance because individuals already have higher levels of existing knowledge that happens to be job-relevant or because having higher levels of existing knowledge (even if it is not directly job-relevant) facilitates learning on the job. However, as mentioned above, matching the content of the narrow ability to the job did not have a significant effect on the validity of cognitive ability. This effect occurred even while controlling for general knowledge, suggesting that the effects of this narrow ability are not job specific either. Therefore, it seems more likely that a high level of general knowledge can help to facilitate learning in a new domain. This is consistent with the phenomenon known as the "Matthew Effect," where individuals with existing advantages (e.g., more job-relevant or general knowledge) receive more resources and more opportunities for growth and development (Call et al., 2015). Future research should examine this issue more closely and explore the potential role of learning in the validity of narrow cognitive abilities.

Implications for Practice

The results of the present study also have several implications for practice. Some have criticized the measurement of cognitive ability because of the narrow range of abilities that are assessed (Ackerman, 1996; Humphreys, 1994; Mount et al., 2008). Many measures of cognitive ability tend to favor narrow abilities like verbal, quantitative, and spatial abilities and exclude other abilities that may be less highly correlated with GMA such as processing speed and visual processing. Although general knowledge is sometimes assessed in cognitive ability measures, this is not common. The present study suggests that the practice of assessing a narrow range of content in cognitive ability measures may limit the potential predictive validity of the assessment. Stated differently, if a cognitive ability test battery only assesses narrow abilities that are highly correlated with GMA, then the battery of tests will provide an efficient estimate of the general factor but may miss the additional predictive validity that can be provided by other narrower abilities. Therefore, organizations that are using cognitive ability measures for employee selection should carefully consider the content of these measures and attempt to assess a broader range of content than has traditionally been assessed.

However, this effort to assess a broader range of cognitive abilities may, in some cases, require a tradeoff between testing time and incremental validity. Assessing a more comprehensive set of narrow cognitive abilities will require longer assessments that take more time to complete. This can be a problem in an employee selection context where testing time may be limited because job applicants are unwilling (or unable) to spend a long time completing assessments for a job. In fact, we expect that the desire for more efficient assessments is at least partially responsible for the tendency to measure a limited range of narrow cognitive abilities in traditional cognitive assessments. To address this issue, while also realizing the potential incremental validity of narrow cognitive abilities, more research is needed to identify the most useful narrow abilities for the employee selection process. The present study takes an initial step towards addressing this issue and the results suggest that narrow cognitive abilities like visual processing, general knowledge, and processing speed added the most to the prediction of performance after accounting for GMA. However, other narrow cognitive abilities that could not be examined here due to an insufficient number of studies that included those abilities in the literature may also be useful. Therefore, more research is needed to examine other narrow cognitive abilities in the CHC model (see Table 1) and to identify those that can provide the greatest utility given the increased amount of testing time required to assess them.

In some cases, assessing a broader range of narrow abilities to improve prediction may not require longer assessments. Some cognitive ability measures already assess several narrow cognitive abilities but their scores are aggregated to reflect GMA rather than the narrow abilities. When this is the case, and especially when the narrow cognitive abilities include those that are less highly correlated with GMA, it may not be necessary to add more items to assess additional narrow cognitive abilities. Instead of examining overall scores, the disaggregate scores for each narrow ability should be examined and used for prediction. This will provide information on a broader range of narrow cognitive abilities that may add incremental validity over GMA and potentially reduce the adverse impact of the cognitive ability measure (Wee, Newman, & Joseph, 2014).

Limitations and Directions for Future Research

As with all studies, the present study has several limitations. One limitation is that we did not have item-level information to estimate the full hierarchical structure of cognitive ability. In other words, we could not estimate a model where both the narrow abilities and the general factor were modeled as latent factors. Therefore, it is possible that the structure of cognitive ability could have differed from the underlying structure we used here. This is a potential limitation because differences in the structure of cognitive ability (i.e., different numbers or types of narrow abilities) could influence the results about which narrow abilities provided more incremental validity. Nevertheless, the narrow abilities examined in this study were based on the widely researched CHC model and, therefore, have strong empirical support (McGrew, 2009).

Another limitation is that we were only able to examine the narrow cognitive abilities that had been examined in previous research. Consequently, some narrow abilities that may be useful for predicting performance were excluded from our study. For example, short-term memory, long-term memory, auditory processing, and reaction and decision speed are all narrow abilities in the CHC model that could not be examined in the present study because we could not find enough relevant studies assessing these abilities in the literature. As shown in Table 2, these abilities have some of the lowest correlations with GMA when compared with other narrow abilities. This would suggest that these narrow abilities could have contributed additional unique variance to the prediction models if they were also correlated with job performance. Future research should continue to expand the measurement of cognitive ability to include a broader range of narrow abilities and explore their incremental validity for predicting performance.

Conclusions

The present study summarizes the last 30 years of research on the relationship between cognitive ability and job performance. Our findings suggest that narrow cognitive abilities can add substantially—beyond GMA—to the prediction of job performance (e.g., task and training performance, organizational citizenship behavior). The incremental validity of narrow cognitive abilities was strongest for those narrow abilities that were the least strongly correlated with GMA. These findings contradict past research and have important implications for the measurement of cognitive ability in employee selection. Based on these findings, we may need to reconsider how cognitive ability is measured, especially in applied settings where tradeoffs are often made between the efficiency and validity of an assessment. We believe that this study provides a first step towards reinvigorating research on the utility of a broader range of cognitive abilities and organizational outcomes.

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