Reexamining the Role of General Cognitive Ability and Specific Abilities in the Prediction of Job Performance Using a Construct-oriented Approach: Not Much More Than *g*?

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(ABSTRACT)

The purpose of the present study was to attempt to reconcile the seemingly overwhelming body of empirical evidence arguing for the preeminence of general cognitive ability in relation to specific abilities with the general resistance of the majority of Industrial-Organizational psychologists to such a position. The contention of the present study was that the primary evidence used to support the view that specific abilities are of little importance relative to general cognitive ability did not faithfully represent the classic selection model and was based on tenuous assumptions about the operationalizations of general and specific cognitive abilities. By virtue of being defined in un-interpretable terms with respect to content or function, prior operationalizations of specific abilities did not lend themselves to logical and theoretical relationships with job specific job performance. The general thesis of the present study was that if a "construct oriented approach" that is largely based on this classic selection model were implemented, a composite of psychologically interpretable job related specific abilities would prove equivalent or even superior to general cognitive ability in the prediction of job performance. Results suggest implementation of the construct oriented approach demonstrates potential for the value of this approach with respect to balancing criterion related validity and social equity.

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Introduction

In a survey of over seven hundred members and fellows of the Society for Industrial-Organizational Psychology (SIOP), Murphy, Cornin, and Tam (2003) found that eighty three percent of these scientists believe that different jobs require different types of cognitive abilities. Moreover, only twenty five percent of SIOP members agree that combinations of specific aptitude tests have little advantage over measures of general cognitive ability in personnel selection. This majority opinion among Industrial-Organizational psychologists has meager support in the scholarly literature. A number of empirical studies have found that specific abilities do not contribute to the prediction of job performance beyond general cognitive ability and suggest that *g* is sufficient for predicting job performance from the cognitive domain (Carretta & Ree, 2000; Jones & Ree, 1998; McHenry, Hough, Toquam, Hanson, & Ashworth, 1990; Olea & Ree, 1994; Ree & Earles, 1991a; Ree, Earles and Teachout, 1994). These studies, as well as others, have been used to foster the idea that specific abilities are essentially unnecessary in the realm of personnel selection (Gottfredson, 2002; Hunter, 1986; Schmidt, 2002; Schmidt & Hunter, 2004; Schmidt, Ones, & Hunter, 1992).

Most of the empirical studies cited as evidence for the superiority of general cognitive ability (relative to specific abilities) in the prediction of job performance operationalize specific abilities in a way that puts them at a severe disadvantage. More specifically, a multi-aptitude cognitive battery (most often the Armed Services Vocational Aptitude Battery) is subjected to a principle components analysis. General cognitive ability is operationalized as the first principle component (i.e. "psychometric *g*") and specific abilities are operationalized as the remaining un-rotated principle components. This methodology does not produce specific ability scales that represent interpretable psychological constructs and is apt to arbitrarily assign items and/or scales with the best psychometric properties (e.g. range, variance and reliability) to general cognitive ability. Moreover, defining general cognitive ability in such a way is purely data driven and all but mathematically ensures the predictive superiority of *g*. Specific abilities are likewise no longer represented as conceptually meaningful variables, but as linear combinations of observed variables orthogonal to the first principle component.

Although the predictive validity of general cognitive ability is without question (Hunter & Hunter, 1984; Schmidt & Hunter, 1998), the contention of the present study is that the principle component methodology common to many studies that compare general cognitive ability to specific abilities does not demonstrate a fair representation of potential contribution of specific abilities to the prediction of job performance. Psychometric *g* suffers from a number of conceptual and methodological shortcomings that cast doubt on its scientific worth (Gould, 1994; Mulaik, 1994; Stankov, 2002). Moreover, general cognitive ability is rarely operationalized as psychometric *g* in actual personnel selection situations. The applied relevance of much of the empirical work that compares *g* to specific abilities is therefore also questionable.

The purpose of the present study is to provide a more scientifically defensible and fair evaluation of the potential for specific abilities to predict job performance. Specific cognitive abilities and general cognitive ability will be compared using a variation of what has been labeled a "construct-oriented approach" (Schneider, Hough, & Dunnette, 1996) and advocated in prior work comparing the predictive value of narrow facets and broad factors of personality (Paunonen & Ashton, 2001; Paunonen, Rothstein, & Jackson, 1999). That is, relationships between specific ability constructs and job performance constructs in a given job will be established a priori based on logical and theoretical consideration of the predictor and criterion. Unlike many of the previous studies that have compared specific abilities to general cognitive ability, specific ability scales will be kept intact as psychologically interpretable constructs rather than arbitrary linear combinations of variables. That is, the present study will consider defining specific abilities in psychological rather than mathematical terms and thereby provide a more comprehensive examination of the relationship between cognitive abilities and job performance. Likewise, the evaluation of general and specific abilities will be conducted on a job-by-job basis rather than collapsing across occupations that may have differing ability requirements.

The present study will address the relative value of general and specific abilities in predicting job performance using data from the Army Selection and Classification Project (Project A; Campbell, 1990). The Project A database is ideal for this purpose because it contains a large number of diverse cognitive measures as well as both objective (work sample) and subjective (supervisor/peer ratings) measures of job performance. In addition to being job specific, the hands on work samples represent uncommonly detailed and precise measures of job performance. The construct-oriented approach will be compared to different operationalizations of general cognitive ability (including psychometric *g*) in nine different military jobs.

The construct-oriented approach has a number of scientific and pragmatic advantages over procedures used in prior research examining the relationship between general/specific abilities and job performance. As a number of researchers have noted (Ashton, 1998; Nunnally, 1978; Paunonen et al., 1998; Schneider et al., 1996), multidimensional composites such as psychometric *g* provide no insight into exactly which dimensions are responsible for prediction in any given job because psychological meaning is lost in general composites. A construct-oriented approach is favorable in this regard because predictors retain conceptual meaning, thereby facilitating a richer theoretical understanding of ability-performance relationships. A construct-oriented approach using specific abilities also has the potential to be preferable from a legal standpoint. If carefully chosen specific ability predictors can exceed or even approximate the validity of general cognitive ability, there is speculation that they will do so with smaller sub-group differences (Kehoe, 2002). If this is indeed true, it would be the preferred approach from the Equal Employment Opportunity Commission's perspective (Uniform Guidelines, 1978).

Definitions of general cognitive ability

The predictive validity of general cognitive ability is so well researched that some have gone as far as to claim that "*g* is to psychology what carbon is to chemistry" (Ree & Earles, 1993) and to draw analogies between *g* and the theories of evolution (Schmidt, 2002) and plate tectonics (Schmidt & Hunter, 2004). Although there is widespread consensus regarding the predictive validity of general cognitive ability, *g* as a psychological construct does not have a single agreed upon definition either in terms of the concept itself or even in how it is to be measured. Nevertheless, a 1994 editorial in the Wall Street Journal published the following conceptual definition with 52 prominent signatories primarily from the field of psychology:

> a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—'catching on,' 'making sense,' of things or 'figuring out" what to do (Gottfredson, 1997b, p.13).

Although this definition is rather nebulous from a scientific perspective, it does capture many of the conceptual aspects central to the construct of general cognitive ability.

The measurement of general cognitive ability also lacks singularity and is perhaps even more indistinct than its conceptualization. Operational definitions of general cognitive ability nonetheless fall into two categories. These categories are primarily a function of the purpose of the research. Most basic or fundamental research on general cognitive ability operationally defines general cognitive ability as psychometric *g*, which is derived from any number of factor analytic techniques (Carrol, 1993). Most applied research, and validity generalization research in particular, largely operationalizes general cognitive ability as the summation of verbal, quantitative and sometimes spatial scales or as a general mental ability test that include such content areas (Hunter, 1986; Pearlman, Schmidt, & Hunter, 1980; Schmidt, 2002.)

Charles Spearman was the first to introduce the concept of general intelligence (Spearman, 1904). The concept of general intelligence, which is now more commonly referred to as general cognitive ability, general mental ability, or simply "*g*," has endured in the psychological literature and become an empirical juggernaut rivaled by few issues in the field. General cognitive ability is a product of Spearman's observation that a number of mental tests with varying content were all positively correlated. Spearman's original model came about by what is now known as factor analysis. His two factor model describes the variance contained in a number of mental tests in terms of a single large general factor and a number of smaller specific factors. In the language of the common factor model, *g* is the variance due to the extraction of one general factor from a large number of ability tests and specific abilities are represented by the variance unique (unique variance is also referred to as "error" variance in the common factor model) to each individual test. General cognitive ability defined by methodologies based on the analysis of a covariance or correlation matrix of a number of diverse cognitive variables is specifically known as psychometric *g*. According to Jensen (2002), psychometric *g* is essentially the "distillation" of a number of cognitive variables via factor analysis.

Spearman's two factor model, interpreted in terms of the common factor model just described, is only one of a number of common ways of modeling psychometric *g* (Jensen & Weng, 1994). The simplest model, which is most commonly used in empirical studies, is the principle components model. Principle components models of psychometric *g* represent a linear combination of the total (common and unique) variance in each of a number of cognitive variables. The first principle component in such an analysis is interpreted as psychometric *g* and the remaining principle components are interpreted as specific abilities. The principle component model of general and specific abilities is unique from all other models in that it is the only model in which *g* and specific abilities are defined as completely orthogonal factors. That is, general cognitive ability is operationalized as the first principle component and specific abilities are operationalized as that which is independent from the first component (and also independent from each other). The benefit of orthogonal components is the capability to clearly separate general and specific factors and thus eliminate colinearity among cognitive variables. Nevertheless, the idea of completely orthogonal general and specific factors is inconsistent with essentially all theoretical and empirical individual difference models of cognitive abilities (Landy & Shankster, 1994; Murphy, 1996).

Another common model is the nested model. Nested factor models first estimate a general factor common to all variables in a matrix. The residual common variance, or variance left over after extracting the *g* factor, is then extracted into orthogonal "group" factors. Mulaik and Quartetti (1997) provide a thorough discussion of nested models of general factors and come to the conclusion that they are inferior to hierarchical models. Hierarchical models are perhaps the most accepted and theoretically appealing way of modeling psychometric *g* (Carroll, 1993). Hierarchical factor analysis models extract group or specific factors such as verbal, quantitative and spatial via common factor analysis. These group factors are referred to as first order factors. After the first order factors are subjected to oblique rotation, the correlations among them are analyzed in order to extract a second order general factor. This higher order general factor is interpreted as general cognitive ability or psychometric *g* (Jensen, 2002; Jensen & Weng, 1994).

Despite the complex theoretical and methodological differences in the various ways of estimating psychometric *g*, different models produce essentially equivalent results when used for the purpose of scoring (Jensen & Weng, 1994). That is, Ree and Earles (1991b) report an average correlation near unity (.984) of psychometric *g* factor scores extracted using 14 different methods. The principle components model is the most commonly used in validity studies that compare general and specific abilities because of its simplicity and practical equivalence (for the purposes of computing factor scores) with other more theoretically appealing models (Ree et al., 1994).

It is worth noting that general cognitive ability is not always defined as psychometric *g* in practice or in research. Indeed, it is more common in personnel selection literature (i.e. validity generalization/meta-analytic studies) and clinical work that general cognitive ability is not derived from a factor analytic procedure. Examination of the enormous body of literature amassed on general cognitive ability or general mental ability reveals that although personnel psychologists and individual difference psychologists often refer to each other's work as referring to the same construct, empirical studies within these domains do not necessarily share a common operationalization of *g*. That is, a number of authors in the personnel selection literature (Hunter, 1986; Pearlman, Schmidt, & Hunter, 1980; Schmidt, 2002; Schmidt & Hunter, 2004) discuss general cognitive ability as the "summation," "combination," or "total score" of a number of tests such as verbal, quantitative and occasionally spatial. Nevertheless, this is distinct from psychometric *g*, which Jensen (2002) explicitly asserts is not the summation or average of scores on diverse tests.

The summation of scores from more narrowly defined scales is the most common operationalization of general cognitive ability in applied settings. Industrial-Organizational psychologists often rely more on shorter general mental ability tests such as the Wonderlic Personnel Test (WPT; Wonderlic, 1992). The WPT, which is the most representative of those used in I-O practice, is described as a factorially mixed measure that combines verbal, quantitative and spatial content to yield a general mental ability total score (Schmidt & Hunter, 2004). The most common measure used by clinical and neuropsychologists is the Wechsler Adult Intelligence Scale (WAIS; Tulsky & Ledbetter, 2000). General mental ability in the WAIS is a summation of fourteen sub-tests, including vocabulary, arithmetic, comprehension and object assembly. For both of the most common measures of cognitive ability (the WPT and the WAIS), general cognitive ability is operationalized as the total score from scales of varying content rather than a "distillation" of psychometric *g* from a series of specific ability measures.

Predictive Validity of General Cognitive Ability

The positive relationship between general cognitive ability or general mental ability (*g*) and job performance is the most robust and enduring outcome of many years of research in Industrial/Organizational psychology (Hunter & Hunter, 1984; Sackett, Schmitt, Ellingson, & Kabin, 2001; Schmidt & Hunter, 1998; Schmidt & Hunter, 2004). The evidence is undeniable; general cognitive ability consistently exhibits a positive relationship with job performance larger than any other single construct (Schmidt & Hunter, 2004). The advent of validity generalization or meta-analysis techniques (Schmidt & Hunter, 1977) has demonstrated that small validity coefficients found in primary studies of general cognitive ability are likely due to artifacts and that *g* has at least some meaningful predictive power for almost every job studied. Hundreds of primary studies and a number of meta-analyses demonstrating the significant relationship between *g* and job performance have proliferated Industrial/Organizational research literature since its inception.

In what is perhaps the most widely cited study regarding the predictive validity of *g*, Hunter and Hunter (1984) reanalyzed a number of prior meta-analyses using their own validity generalization techniques. In their reanalysis of Ghiselli's (1973) study on the mean validity of cognitive ability, they found estimated true validity coefficients, which are corrected for unreliability of the criterion and range restricted predictors, ranging from .61 to .27. In general, higher validities were associated with higher job complexity. Hunter and Hunter (1984) also report validity coefficients for general cognitive ability as measured by the General Aptitude Test Battery (GATB) from a technical report conducted by Hunter for the United States Department of Labor in 1980. The estimated true validity coefficients in these analyses range from .50 to .65 for training success and .23 to .52 for job performance. Again, higher validities were found in jobs classified as more complex. The average estimated true validity for *g* across all jobs was found to be .54 for training success criterion and .45 for job performance criterion.

The same data from Hunter and Hunter (1984) were reported again in Schmidt and Hunter (1998) in a slightly different form. The authors report the overall estimated true validity of *g* to be .51, which is noted as the average validity for medium complexity jobs. They also report the estimated true validity of *g* to be .58 for professional-managerial jobs, .56 for high level complex technical jobs, .41 for semi-skilled jobs and .23 for completely unskilled jobs. Schmidt and Hunter (1998) conclude that *g* should be considered the primary selection measure in any hiring situation because it has the highest validity, lowest cost, largest body of empirical work, and strongest theoretical backing at the construct level.

Hunter (1986) summarizes analyses from large scale validation studies (n= 472,539) conducted by the United States Military, which report average estimated true validity coefficients for training success ranging from .58 to .67. Hunter (1986) also reports corrected correlations between *g* and objective measures of job performance (work samples) to be .75 and .53 in civilian and military samples, respectively. In the same analyses, the corrected correlation between *g* and supervisor ratings of job performance was found to be .47 in a civilian sample and .24 in a military sample. Path analysis of these data lead to the conclusion that the relationship between *g* and job performance is largely mediated by job knowledge, but that *g* also has a direct effect on job performance. That is, individuals higher in general cognitive ability acquire more job knowledge, which in turn leads to higher job performance.

The relatively large validity coefficients of general cognitive ability have also been found in studies conducted in Europe. Salgado, Anderson, Moscoso, Bertua, Fruyt and Rolland (2003) meta-analyzed the validity of *g* in a number of different occupations in European samples. They report estimated true validity coefficients ranging from .24 for police officers to .67 for managers when job performance ratings were the criterion. Estimated true validity coefficients ranged from .25 for police officers to .74 for engineers when training success was the criterion. Salgado et al.'s (2003) results also indicate that job complexity moderates the relationship between g and job performance such that validity is higher for more complex occupations.

In a separate paper that analyzes essentially the same data, Salgado, Anderson, Moscoso, Bertua and Fruyt (2003) collapse across occupation and examine the validity of *g* and more specific cognitive abilities such as verbal, numerical and spatial. General cognitive ability demonstrated the highest estimated true validity coefficient for predicting both performance ratings and training success (.62 and .54 respectively). The authors claim that .62 is the highest estimated true validity coefficient reported in any meta-analysis for a single selection method. The overall conclusion of the studies conducted on European samples is that the massive body of validity evidence for *g* generalizes to the European community.

In the most recent meta-analytic effort, Kuncel, Hezlett, and Ones (2004) examined the validity of one particular measure of general cognitive ability, the Miller Analogies Test (MAT), for predicting a variety of academic and work related criteria. They found estimated true validities for academic criterion such as graduate grade point average, faculty ratings and comprehensive exam scores to be .34, .37 and .58, respectively. The MAT was found to have an estimated true validity coefficient of .41 for job performance. Kuncel et al (2004) note that although the MAT is designed and primarily used in academic applications (i.e., graduate school entrance), it is a valid predictor of job performance as well. This dispels the notion that *g* less important in “real world” work settings.

There are also a number of validity generalization or meta-analytic studies conducted on specific job families (e.g. clerical, computer programming, and craft work) that find *g* has the highest validity of any single predictor. Pearlman, Schmidt, and Hunter (1980) examined the validity of a number of cognitive predictors for clerical jobs and found *g* to have the highest estimated true validity (.52 for job performance and .71 for training success) across all clerical jobs studied. Schmidt, Gast-Rosenberg, and Hunter (1980) found estimated true validities of the Programmer Aptitude Test (PAT) to be .73 for job performance and .91 for training success. Although the PAT is not explicitly a measure of general cognitive ability, it fits Hunter (1986) and Schmidt’s (2002) definition of any measure that combines or sums across two or more specific aptitude scales. Levine, Spector, Menon, Narayanan, and Cannon-Bowers (1996) found cognitive measures to have the highest estimated true validity (.43 for job performance and .67 for training success) for craft jobs in telecommunication industry.

However, two meta-analyses of predictive validities conducted on specific job families have found validity coefficients for *g* to be rather small in relation to the studies already mentioned. Hirsh, Northrop, and Schmidt (1980) found mean observed validities of two different operationalizations of *g* to be .12 and .16 for law enforcement jobs. Similarly, Vinchur, Schippmann, Switzer and Roth (1998) found the estimated true validity of *g* to be .40 for job performance ratings, but only .04 for an objective measure of job performance (sales volume) for salespeople. Hirsh et al. (1980) speculate that personality may be a more valid predictor of job performance given the nature of law enforcement work and Vinchur et al. (1998) actually found "Big Five" personality facets (achievement) and broad dimensions (conscientiousness and extraversion) to have the highest validity coefficients for sales people when sales volume was the criterion.

The empirical evidence demonstrating the relatively superior predictive validity of general cognitive ability is nearly unquestionable and seemingly ubiquitous. The meta-analyses just reviewed summarize validity data from hundreds of studies on hundreds of thousands of individuals that are generally in consensus. A common finding among the majority of validity studies is that the predictive validity of *g* increases with job complexity. General cognitive ability can be simply defined as the ability to deal with cognitive or information processing complexity (Gottfredson, 1997a). Because of the inherent complexity of job performance, it is this ability to make sense of and solve complex problems that makes *g* theoretically relevant to performance on the job (Gottfredson, 2002). *G* is the most important determinant of job knowledge acquisition, which in turn is an important determinant of job performance (Hunter, 1986; Schmidt & Hunter, 2004). General cognitive ability also has a direct effect on job performance such that individuals higher on *g* are better able to deal with fluid complexities such as reasoning and decision making involved in performing any number of job tasks (Gottfredson, 1997b).

Definition of Specific Abilities

Perhaps the most comprehensive taxonomy of abilities has been developed by Fleishman and his colleagues (Fleishman, 1975; Fleishman & Quaintance, 1984; Fleishman & Reilly, 1992). Abilities are conceptually defined in this paradigm as the capacity or general trait of an individual that is related to performance of human tasks. Fleishman and associates have identified 52 conceptually and empirically distinct human abilities in an expansive research program. Among them are 21 cognitive abilities, 10 psychomotor abilities, 9 physical abilities and 14 perceptual abilities (Fleishman & Reilly, 1992). These abilities were identified and defined under the paradigm of Fleishman's abilities requirements approach (Fleishman, 1975; Fleishman & Quintance, 1984). Their description and differentiation arose out of an iterative series of experimental and factor analytic studies in which abilities are inferred from individual propensities in performing related tasks.

The abilities identified through Fleishman's research have been influential in such projects as the Army Selection and Classification Project (Project A) and the development of the O*net (Peterson, Mumford, Borman, Jeanneret & Fleishman, 1999; Russell, Peterson, Rosse, Toquam, McHenry, & Houston, 2001). His taxonomy is thus the most comprehensive and widely used framework for the description and differentiation of human abilities.

Predictive Validity of Specific Cognitive Abilities

The preponderance of evidence in support of the predictive validity of general cognitive ability has not completely precluded research examining the predictive validity of more narrowly defined specific cognitive abilities (e.g. verbal ability, quantitative ability, spatial ability, memory). The majority of this research, which has primarily compared the validity of specific abilities (*s*) in relation to the validity of *g*, has been conducted by Ree and colleagues (Carretta & Ree, 2000; Jones & Ree, 1998; Olea & Ree, 1994; Ree & Earles, 1991a; Ree, Earles & Teachout, 1994). All of these studies share a common methodology for operationalizing *g* and *s*, in which a cognitive test comprised of a number of sub-tests (e.g., verbal, mechanical, quantitative) such as the Armed Services Vocational Aptitude Battery (ASVAB) is subjected to a principle components analysis. General cognitive ability is operationalized as the first unrotated principle component and specific abilities are operationalized as the remaining unrotated principle components resulting from this analysis.

Ree and Earles (1991a) analyzed the validity of *g* and *s* (derived from the ASVAB in the manner just described) in predicting final grades in training courses for over 78,000 Air Force enlistees. Their results indicated that specific abilities account for statistically significant variance in training success beyond the variance explained by *g*, but that this increment is small in practical terms (i.e., increase in *R* between .005 and .02 with an average of .012). The largest gain in predictive efficiency was found when the *s* components were allowed to be optimally weighted for each job, but the gain was nevertheless trivial in practical terms. Similar results were obtained by Ree et al. (1994) in predicting job performance of over 1000 Air Force enlistees. General cognitive ability and specific abilities were derived from principle components analysis of the ASVAB. Specific abilities again added statistically significant, but practically small increments of variance explained in job performance beyond that explained by *g*. Across all jobs studied, the largest multiple *R* gain for *s* above *g* was .035 when a hands-on performance test was the criterion. Multiple *R* gains of .007 and .021 were found for interview work sample test and walk-through performance test criterion, respectively. Olea and Ree (1994) once again found comparable results in their analysis of the predictive validity of *g* and *s* (derived from the Air Force Officer Qualifying Test; AFOQT) in predicting a number of pilot and navigator criteria, including objective work sample tests. The average multiple *R* gain across all criterion measures for *s* beyond *g* was .02 for navigators and .08 for pilots. Incremental variance explained by specific abilities beyond that explained by general cognitive ability ranged from .006 to .104.

Carretta and Ree (2000) summarize a number of studies including the ones just reviewed in which the predictive validity of specific abilities is compared to that of general cognitive ability. They conclude, based on a number of studies using the same basic methodology for operationalizing *g* and *s*, that specific abilities contribute little to no meaningful variance in explaining job performance or training criterion. They go on to note that similar results have also been obtained for tests of psychomotor ability, which are related but distinct from cognitive abilities. That is, psychomotor ability contributes little to no meaningful variance in job performance beyond that which is already explained by *g*.

A few of the meta-analyses already reviewed examined the predictive validity of selected specific abilities independent of *g*. Salgado, Anderson, Moscoso, Bertua and Fruyt (2003) report that specific cognitive abilities such as memory and numerical ability demonstrated estimated true validities of .56 and .52 respectively when job performance ratings were the criterion and .34 and .48 when training success was the criterion. Verbal, spatial-mechanical, and perceptual abilities were reported to have estimated true validities of .35, .51 and .52 for job performance rating criterion, respectively and .44, .40 and .25 for training success criterion, respectively. Pearlman et al. report estimated true validities across clerical jobs for verbal (.39), quantitative (.47), reasoning (.39), perceptual speed (.47), memory (.38) and spatial/mechanical abilities (.30) for job performance criterion. Some of the validity coefficients reported for specific abilities in isolation are not appreciably lower than the coefficients for general cognitive ability. For some jobs or job families, the validity coefficient for a single specific ability was higher than the validity coefficient for *g*. For example, Pearlman et al (1980) report the estimated true validity for reasoning ability is .63 (compared to .49 for general cognitive ability) in computing and account recording occupations. This is particularly noteworthy given that measures of *g* are almost always a summation or amalgamation of a number of different specific abilities.

Dissatisfaction with psychometric g

Despite the undeniable predictive utility of general cognitive ability (however it may be defined), many scholars remain dissatisfied with and even wholly resistant to the construct (McClelland, 1993; Sternberg & Wagner, 1993). Criticisms of *g* come from both conceptual (Ceci, 2000; Goldstein, Zedeck, & Goldstein, 2002; Murphy, 1996; Stankov, 2002) and mathematical points of view (Guttman, 1992; Maraun, 1996; Mulaik, 1994; Schonemann, 1997). Because psychometric *g* is by definition a product of factor analytic techniques, conceptual and mathematical or methodological critiques of the construct are not entirely independent from one another. Nevertheless, scholarly works that question the primacy or even existence of *g* typically do so from either a conceptual or methodological perspective.

A number of authors have observed that scholars cannot agree on a common conceptual definition of *g* (Lubinski, 2004; Neisser, Boodoo, Bouchard, Boykin, Brody, Ceci, Halpern, Loehlin, Perloff, Sternberg & Urbina, 1996). Goldstein et al (2002) note that although there is clear overlap between definitions of *g*, scholars tend to arbitrarily add or remove skills or aptitudes that fall under the rubric of *g*. As alluded to in the discussion of the definitions of general cognitive ability, there are almost as many operational and conceptual definitions of *g* as there are studies dealing with the construct. The fact that a construct is so ubiquitously referred to in the literature, yet with such little convergence in its definition is inherently troublesome.

The lack of agreement is to some extent the result of a lack of scientific understanding of the fundamental psychological processes underlying general cognitive ability. A single process underlying general cognitive ability has yet to emerge and furthermore is unlikely to emerge because of the broad and general nature of the construct. This may be a function of the fact that in hierarchical models (Carroll, 1993), which are arguably the most theoretically appealing and widely accepted representations of *g*, the highest order factor is three-times removed from test items or scores that are psychologically interpretable (Stankov, 2002). Deary, Austin, and Caryl (2000) point out that there is a considerable lack of overlap between efforts to measure cognitive abilities and scientific efforts to understand the process by which they arise. The psychometric approach to intelligence or general cognitive ability can only escape its tautological status by establishing connections between measurement and underlying processes.

Advances in cognitive science and neuroscience that attempt to *explain* intelligence (rather than relegating it to a poorly defined tautology) through a neural plasticity model are inconsistent with the existence of a general factor (Garlick, 2002). Although this research is relatively young and in need of further empirical work, the theory is superior from a scientific perspective in that the process of intelligence is not confounded with its definition. That is, neural plasticity (the process of neural network connectivity and adaptation to stimuli/environment) has been offered as an alternative explanation for individual differences in intellectual ability. According to this theory, positive manifold among traditional measures of cognitive ability can be explained by the evolution of measures selected for their lack of environmental variance. The model of neural plasticity is consistent with many of the findings in intelligence research but goes beyond sole reliance on positive manifold by positing a causal mechanism for individual differences in intellectual ability.

Empirical and theoretical work on neural plasticity discussed by Garlick, (2002) may or may not become as widespread and mainstream as that on psychometric *g*. Nevertheless, this example is important because it calls attention to the fact that causal processes are conspicuously absent from existing models of intelligence (e.g. Carroll, 1993) and general cognitive ability itself. Borsboom, Mellenbergh, & van Heerden (2004) argue that the traditional concept of construct validity (Cronbach & Meehl, 1955; Messick, 1995) is tenuous because of the over-reliance on correlations and under-reliance on true causal models. This criticism is particularly relevant to general cognitive ability because of the absence of any specification of an underlying process and because of the circular and tautological nature of its definition. Although the model of neural plasticity does not have the backing of over 100 years of psychometric research, it does have the advantage of fitting a causal model that contains a true definition and a theoretical explanation for individual differences in intellectual functioning.

Even within traditional paradigm of construct validity, Psychometric *g* is commonly criticized for being overly parsimonious from a conceptual standpoint (Gould, 1994; Murphy, 1996; Stankov, 2002). Although one of the primary functions of factor analytic methods is data reduction, psychometric *g* is often viewed as an over-simplification that results in the loss of meaningful and important distinctions among cognitive abilities. Collapsing across abilities will result in significant loss of information with regard to individual differences in specific abilities.

For example, Fleishman and associates have identified 21 conceptually distinct cognitive abilities in a number of experimental and factor analytic studies (Fleishman & Reilly, 1992). Moreover they have amassed a large body of job analytic work demonstrating differential relationships between abilities and performance of job related tasks (Fleishman, 1975; Fleishman & Mumford, 1991; Fleishman & Quaintance, 1984; Fleishman & Reilly, 1992). The exclusive use of general cognitive ability for the prediction of job performance does not allow the observable manifestation of these distinct abilities or their differential relationships across jobs.

A number of scholars have taken issue with the over-reliance and often unconsidered use of factor analysis as the defining mechanism of a psychological construct. Because psychometric *g* is derived by factor analyzing a number of cognitive tests designed to measure more narrowly defined abilities, *g* will necessarily vary based on the collection of tests from which it is derived (Bowman, Markham, & Roberts, 2002; Horn, 1985). That is, g is not a singular construct because it is almost always derived from a biased sample of the universe of cognitive measures (Stankov, 2002). Nevertheless, psychometric *g* is often discussed as if it is isomorphic across operationalizations. This lack of singularity is particularly egregious in the personnel selection literature. Validity generalization studies assume that different measures of *g* are assessing the same construct (Bowman et al. 2002).

Horn (1985) is particularly critical of the principle component methodology used by many researchers (e.g., Jensen, 1980). He argues that psychometric *g* is often arbitrarily defined from one empirical occasion to another. The first principle component derived from one set of measures represents a different mixture or distillation of abilities than the first principle component from another set of measures. More importantly, the first principle component extracted from an arbitrary collection of ability measures does not necessarily produce a construct that can be interpreted as general cognitive ability. That is, the first principle component (or common factor) does not necessarily represent “the ability to deal with complexity” or any other extant conceptual definition of *g*. Similarly, Horn argues that the first principle component is more analogous to a conglomerate than a compound and that a conglomerate or linear combination of abilities does not necessarily represent a unitary construct.

A fundamental aspect of the rationale for the existence of general cognitive ability is the positive manifold phenomenon (i.e. that nearly all cognitive measures are at least somewhat positively correlated), which is the original basis of Spearman’s (1904) general intelligence construct. A number of scholars have argued that positive manifold alone is not sufficient evidence for the existence of general cognitive ability. A common argument is that it is possible to extract a first principle component or factor that explains a large percentage of variance from a number of arbitrary and conceptually distinct variables. Horn (1985) notes that a number of non-cognitive variables, such as athletic ability, emotional stability, and openness also exhibit positive manifold with cognitive ability measures. Bowman et al. (2002) argue that although positive manifold can be found in the Five Factor model of personality (assuming neuroticism is reversed), scholars in this field recognize the structural independence of personality constructs. That is, no one has advocated a general personality construct and conceptualization of such an entity is difficult to imagine or defend. Similarly, Shonemann (1997) found positive manifold in, and was able to extract a general factor from a series of seemingly arbitrary “toy variables.” That is, a general factor was extracted from a measure that children in the head start program responded to regarding how many toys, games or books a child owns as well as how often he or she uses these items.

The preceding findings are relevant to the argument that psychometric *g* represents a reification of a mathematical artifact (Gould, 1996). Gould argues that although strong principle components can and do represent real and meaningful entities, the mere existence of a strong component or factor is not evidence of the existence of something with true meaning. The fact that a number of variables are correlated does not necessarily reveal anything regarding the cause of their inter-relatedness. Indeed, there are often a number of plausible explanations for why a set of variables might be related. Moreover, their interrelatedness does not necessarily require that they represent anything real. Similarly, a strong first principle component or factor does not require the existence of a meaningful construct. Principle components, factors and correlations in and of themselves reveal nothing about causality. According to Gould, psychometric *g* has been erroneously reified because there is no underlying or independent causal explanation for the positive relationship among variables. All that can be said is that there is a correlation among the variables, and conspicuously absent is a sufficient explanation (independent of their inter-relatedness) for why they are related. Psychometric *g* has therefore been labeled a tautology in that its explanation is confounded with its definition (Deary, 2000; Michell, 1999).

Mulaik (1994) has leveled a similar criticism against principle components analysis in general. He argues that it is a mistake to attribute underlying causality to the first principle component merely upon its existence because it is a purely mathematical entity. The first principle component represents specific linear combination of observed variables that contains the maximum variance of any possible combination and is not interpretable as a latent variable. Thus, attempting to uniquely interpret what is common among a set of variables using principle components analysis is problematic because nearly every variable in the matrix will have a moderate to strong correlation with the first principle component. Moreover, it remains possible that the first principle component is an artifact imposed by the method of analysis. The first principle component is a linear combination of variables that satisfies a mathematical criterion. This criterion will be satisfied regardless of what has been analyzed and thus does not necessarily represent a meaningful psychological construct or objective counterpart (Mulaik, 1994).

Another common and related argument has to do with the arbitrary nature of the solution to principle component or common factor analysis. Gould (1996) claims psychometric *g* is "merely a meaningless average based on the invalid amalgamation of [different] types of information" (p. 283). That is, principle components and common factor analysis often obscure clusters of distinct and meaningfully related variables when a dominant unrotated first component or factor is extracted. For example, Gould articulates two of many possible component or factor solutions in a matrix of two mathematical and two verbal variables. One solution is to extract a general factor or component that "splits" down the middle of the four ability vectors in addition to a second residual factor or component. A second possible solution, which results in no loss of information from the first, is to rotate the factor axes and extract two psychologically interpretable (verbal and mathematical) components or factors. The arbitrary decision of the first solution over the second is not evidence for the existence of a general cognitive ability construct. Indeed, the second solution has more scientific and theoretical merit because the factors are psychologically interpretable based on their content.

It is clear that many scholars are critical and even dismissive of psychometric *g* because of its attempt to derive meaning solely from correlations or correlation based analyses. The scientific merit of psychometric *g* is often called into question because of its inductive, non-falsifiable, arbitrary and amorphous definition as the first principle component of an infinite matrix of ability variables (Guttman, 1992; Schonemann, 1992). Psychometric *g* is by definition a product of purely mathematical techniques that are not appropriate for defining psychological constructs in and of themselves or in the absence of interpretation (Guttman, 1992; Maraun, 1996; Michell, 1999; Mulaik, 1994; Schonemann, 1990, 1997). Equating general cognitive ability (as a real and meaningful construct) with the first principle component or common factor represents data driven sophistry rather than sound scientific reasoning (Guttman, 1992; Mulaik, 1994; Schonemann, 1990). Psychometric g has survived over a hundred years of empirical study not because of its scientific merit, but because of its inherent expedience and utility.

General cognitive ability and specific abilities

Both conceptual and methodological criticisms of psychometric *g* are indeed relevant to empirical studies conducted by Ree and colleagues (Carretta & Ree, 2000; Jones & Ree, 1998; Olea & Ree, 1994; Ree & Earles, 1991a; Ree, Earles & Teachout, 1994) that evaluate the relative contribution of general cognitive ability and specific abilities in predicting job performance. The conclusion of this program of research is that sufficient prediction of job performance, training success and other job related criteria requires “not much more than g.” Although the practical utility, expedience and parsimony apparent in these studies is without question, the decision to operationalize general cognitive ability as the first principle component and specific abilities as the remaining components is of questionable scientific value. Murphy (1996) recognizes that the treatment of specific abilities in these studies “is at best off hand” (p. 7) and contributes little to the understanding of the relationship between job-performance and abilities.

The first principle component is a linear combination of observed variables that satisfies the mathematical criterion of accounting for the most variance in the matrix of those observed variables. As a result, specific abilities in the Ree and colleagues studies are arguably operationally defined as psychometric waste. The specific ability variables (i.e., the remaining principle components) are simply linear combinations of the observed variables that satisfy the mathematical criterion of being orthogonal to the first principle component and do not represent psychologically interpretable constructs. It is therefore unreasonable to come to the conclusion that "specific abilities" account for little to no variance in job performance or other criteria in relation to psychometric *g* when the methodology used to address the issue virtually ensures that very outcome. Assuming the positive manifold phenomenon found in cognitive measures, the outcome of Ree and colleagues studies is more analogous to a demonstration of a mathematical certainty than an empirical hypothesis test.

To their credit, Ree and colleagues recognize and remind the reader that principle components are mathematical abstractions and do not represent constructs with psychological meaning. Nevertheless, their research program has been widely cited in the literature, in the absence of this context, as evidence that specific abilities do not contribute uniquely beyond general cognitive ability in the prediction of job related outcomes. It is perhaps more accurate and appropriate, although somewhat unwieldy, to state the conclusion in the mathematical terms in which the variables were operationalized. That is, linear combinations of observed variables that are orthogonal to a primary linear combination of variables that accounts for the most variance in a matrix of cognitive ability measures do not account for much variance in job performance beyond this first principle component. Although such a statement is clearly cumbersome, the conclusions drawn from Ree and colleague's analyses appear to tacitly assume isomorphism between mathematical entities and psychologically meaningful constructs. The current scientific status of psychometric measurement does not warrant such an assumption. That is, there is no scientific evidence that psychometric *g* represents a fundamental psychological process and simply no logical reason for the equivalence of specific abilities and left over principle components. It is difficult to imagine from a psychological or scientific perspective, how or why a mathematically defined linear combination of variables could possibly represent a psychologically meaningful specific ability (i.e., verbal, quantitative or spatial ability) in the absence of any attempt to interpret it as such. Operationalizations of specific abilities and general cognitive ability in the series of studies conducted by Ree and colleagues have somehow made the leap from mathematically defined entity to psychological construct without sufficient evidence that such a leap is warranted. If variables are operationalized in purely mathematical terms without regard for content and meaning, it seems reasonable that the conclusions derived from those operationalizations must stay in the original mathematical terms. It appears that Ree and colleagues studies have been interpreted as if the mathematical entities analyzed somehow have conceptual or psychological status as “specific abilities.”

Another shortcoming of existing literature comparing general and specific abilities is that the *g* vs. *s* controversy addressed in the series of studies conducted by Ree and colleagues is rather arbitrarily defined. Because *g* is an amalgamation of more narrowly defined cognitive abilities, it is it would be just as well to turn the question around and look at what *g* explains in relation to these more substantively meaningful abilities (Murphy, 1996). A number of researchers interested in personality correlates of job performance have shared a similar sentiment. This argument has gone beyond speculation and been empirically evaluated in the personality literature.

Alternative approach

The use of aggregate or “higher order” predictors such as *g* is not limited to the cognitive domain. Ones and Viswesvaran (1996) endorsed and ostensibly demonstrated the predictive superiority of broad personality traits over more narrowly defined personality facets. Their argument was that job performance is a broad, multiply determined and factorially complex construct which therefore ought to have the strongest relationship with broad and factorially complex non-cognitive predictors. Additionally, they argue that narrow or specific non-cognitive predictors are inappropriate for predicting anything other than narrow and specific criteria. Ones and Viswesvaran (1996) presented data from a number of meta-analytic studies, including Barrick and Mount's (1991) widely cited meta-analysis on the predictive validity of the Big Five personality constructs, that they interpreted to be evidence that broad personality traits are better predictors of job performance than narrow personality facets. Furthering the position of "broader is better," Ones and Viswesvaran (1996) argued that a linear combination (analogous to psychometric *g* and based on positive manifold) of conscientiousness, agreeableness and emotional stability as measured by integrity tests has the highest validity of any non-cognitive predictor. Ones and Viswesvaran (1996) also conclude that broad personality traits are also superior for the purpose of theory building in Industrial Organizational Psychology. According to them, the use of narrow facets of personality would be unwieldy because it would necessitate constructing individually tailored theories of work behavior for each job.

Despite the seemingly intuitive appeal of Ones and Viswesvaran's (1996) arguments, their article was met with a series of scathing responses from conceptual, methodological and empirical perspectives (Ashton, 1998; Hogan & Roberts, 1996; Paunonen, 1998; Paunonen & Ashton, 2001; Paunonen, Rothstein, & Jackson, 1999; Schneider, Hough, & Dunette, 1996). Schneider et al (1996) contend that the use of Barrick and Mount's (1991) meta-analytic data to compare the validity of broad and narrow personality constructs underestimates the validity of narrow facets because it represents a "broadside" approach to criterion-related validity. That is, meta-analyses “can mask personality-performance relationships because validity coefficients associated with predictor-criterion pairings where no relationship is expected on rational or empirical grounds are put into the same category with predictor criterion paring where a relationship is expected (p.642).” Schneider et al. (1996) instead advocate the use of what they label a “construct-oriented” approach adapted from Hollenbeck & Whitener (1988). This involves a priori specification of predictor-criterion relationships based on the relevance of a number of specific or narrow traits to meaningful aspects of job performance. They argue that this approach, in contrast to examining correlations between aggregate composites, enhances both scientific understanding and criterion-related validity.

Schneider et al. (1996) and Paunonen et al. (1999) demonstrate the utility of using a construct-oriented approach using Ones and Viswesvaran’s (1996) own data. Examination of individual correlations, as opposed to the average correlations that Ones and Viswesvaran choose to interpret, reveals that in some instances the broad Big Five factors were actually better predictors of narrow criteria than they were of broad criteria. Moreover, it is the very instances in which the personality variables are theoretically related to a specific job dimension that the correlations are larger than those between Big Five constructs and the broad composite of job performance. Paunonen et al. (1999) go on to note that Ones and Viswesvaran (1996) selectively report fully corrected (corrected for both criterion and predictor unreliability) validity coefficients and it is the very coefficients that were not corrected that demonstrate the predictive superiority of narrow facets of personality.

An empirical study by Paunonen (1998) has also provided evidence for the value of narrowly defined non-cognitive predictors in relation to broad factors in the prediction of various behavioral criteria. In two independent data sets, Paunonen (1998) regressed a number of criteria, such as grade point average, smoking behavior, and dating behavior, on broad big five factors (measured by the NEO-FFI; Costa & McCrae, 1992) and more narrowly defined trait scales (measured by the Personality Research Form; PRF; Jackson, 1984) and Jackson Personality Inventory; Jackson, 1976). His results indicate that in both samples the narrow facets explained more variance in the criteria than the broad facets. In addition, he found that the narrow facets explained more incremental variance beyond the broad factors than the broad factors explained beyond the facets. Paunonen concludes that his study is empirical evidence that factorial complexity of predictors and criterion need not match in order for validity to be optimized. Moreover, he argues for Nunnally's (1978) position that factorial complexity should not be built into omnibus predictors. Rather, factorial complexity in predictors should be obtained by combining regression weighted facets that are theoretically related to the criterion.

This contention was put to further empirical test in a study by Paunonen and Ashton (2001), which demonstrated the predictive value of narrow personality facets in relation to broad factors as well as the construct-oriented approach advocated by Nunnally, (1978) and Schneider et al. (1996). Paunonen and Ashton (2001) again compared the predictive validity of broad factors and narrow facets in the prediction of criteria such as dating, traffic violations, employment and obesity. Subject matter experts were asked to rate the expected association between the narrow facets of personality and each of the criteria. Each criterion was then regressed on the five highest rated facets and then in a separate equation on the five broad factors. Their results indicate that the theoretically matched narrow facets did as well as or better than the broad factors in predicting the criteria. In addition, the narrow facets were able to provide statistically and practically (i.e., up to 18%) significant incremental variance beyond broad factors.

The reviewed conceptual and methodological arguments against Ones and Viswesvaran (1996) (which are corroborated by empirical evidence) suggest that they are wrong in their assertion that broad or general non-cognitive predictors are *necessarily* superior to more narrowly defined facets in the prediction of job performance and other criteria. Moreover, their contention that broad or conglomerate factors are to be preferred from a theory building perspective is also tenuous. Schneider et al. (1996) observe that a substantial amount of knowledge is lost in excessive generality and aggregation. That is, a small number of researchers working under a common paradigm have explicitly or tacitly endorsed the use or measurement of general factors in cognitive (Schmidt & Hunter, 2004) and non-cognitive (Ones & Viswesvaran, 1996) predictors as well as in the criterion of job performance (Viswesvaran & Ones, 2000). The rationale for a general factor in each of these domains is almost exclusively based on positive manifold. Although this assertion is difficult to argue with at a very high level of abstraction, it inherently glosses over a great deal of potentially useful information. Excessive aggregation of cognitive, non-cognitive, and job performance measures has the potential to obscure substantively meaningful relationships between predictor and criterion constructs. Linear combinations or composite predictors are often ambiguous and un-interpretable. This lack of interpretability obscures exactly which facets of the predictor composite are related to which aspects of the criterion variables (Paunonen et al., 1999).

It is likely that many of the same arguments in favor of using a construct-oriented approach in the personality domain also apply to cognitive variables. Unfortunately, no empirical studies exist that directly address the issue. This is partly a result of the suggestion that specific abilities account for little to no variance beyond general cognitive ability. Nevertheless, the studies cited as evidence for this (Carretta & Ree, 2000; Jones & Ree, 1998; Olea & Ree, 1994;

Ree & Earles, 1991a; Ree et al., 1994) employ a decidedly non-construct-oriented approach. Other arguments against using an approach in which abilities are tailored to job performance criteria on a job by job basis is that doing so is expensive, inconvenient and laborious (Jones & Ree, 1998; Ones & Viswesvaran, 1996). Although these are valid arguments from a pragmatic perspective, they do not preclude investigation of the potential effectiveness of a construct oriented approach for scientific and theory-building purposes. Furthermore, because of the contentious social issues surrounding the use of general cognitive ability in employment selection (Sackett et al., 2001) it is worth exploring the possibility that a construct-oriented approach with specific abilities may approximate the predictive validity of general cognitive ability with lower sub-group differences (Kehoe, 2002).

Kehoe (2002) does not provide a rationale for why specific abilities would be expected to produce smaller sub-group differences. Nevertheless, measures of general cognitive ability produce relatively large black-white differences (i.e. one standard deviation) and this difference tends to grow larger with the more comprehensive and accurate measurement of g (Gottfredson, 2002). That is, "better" measures of *g* tend to produce larger disparate impact. By virtue of containing less variance due to general cognitive ability while at the same time being predictive of job performance, (Salgado, 2003) specific abilities are not likely to produce black-white differences of the magnitude found in measures of *g*. Theoretical or empirical work addressing why variance due to specific abilities might produce smaller sub-group differences are absent from the literature. Perhaps individual differences in aptitudes specific to particular tasks develop through different processes than those measured by general cognitive ability tests. These processes may be less dependent on acculturated knowledge and formal education that what is measured by cognitive ability tests. Individuals may also differentially develop specific or specialized aptitudes through exposure to culturally relevant stimuli. Whatever the reason, if specific ability measures are of comparable predictive validity they are to be seriously considered as a substitute for *g*.

Present study

Despite the implication of many validity generalization studies and review articles (Schmidt, Ones, & Hunter, 1992) that general cognitive ability is the only cognitive variable needed to maximize prediction of job performance, there is some evidence to suggest that ability requirements differ across occupations. Prediger (1989) demonstrates that different specific cognitive and non-cognitive abilities are relevant to primary work tasks or behaviors in different occupations and that the exclusive use of general cognitive ability obscures these patterns. Over twelve thousand occupations found in the Dictionary of Occupational Titles were sorted into six job clusters similar to Holland's (1985) occupational groups. Four out of fifteen available specific abilities were assigned to each of the six job clusters based on, among other considerations, the logical relation between specific abilities and work tasks that define a particular job. Prediger's (1989) results indicate that despite using only six job clusters to represent over twelve thousand different occupations, there was substantial variability and diversity in ability ratings for each cluster. In addition, ability rating patterns were logically relevant to the work tasks that define each job cluster. That is, both job task performance and abilities are defined in terms of behavior. The former is defined in terms of what an individual must do in order to perform on the job and the latter is defined in terms of what an individual can do. The exclusive use of general cognitive ability as a predictor of job performance obscures these logical and theoretical relationships. Although Prediger's (1989) study provides insight into the varying relationships between specific abilities and job performance, because it is based solely on ratings of ability performance associations it does not provide evidence directly relevant to the value of specific abilities in predicting job performance.

In what is seemingly contrary to Prediger's (1989) findings, consensus in the personnel selection literature suggests that predicting job performance from the cognitive domain requires little more than general cognitive ability. Nevertheless, the primary source of this empirical finding comes from the series of studies conducted by Ree and colleagues (Carretta & Ree, 2000; Jones & Ree, 1998; Olea & Ree, 1994; Ree & Earles, 1991; Ree et al. 1994) that employ purely mathematical operationalizations of general and specific abilities. This methodology is particularly disadvantageous to specific abilities, which do not represent psychologically meaningful constructs when operationalized as residual principle components. Moreover, general cognitive ability operationalized as psychometric *g* suffers from a number of conceptual and methodological limitations. Also worthy of consideration is the finding in the non-cognitive domain that specific facets can predict as well as general factors when they are theoretically linked to the criterion (Paunonen & Ashton, 2001; Schneider et al., 1996). This construct-oriented approach that has been advocated for non-cognitive predictors has yet to be fully explored in the realm of cognitive abilities.

The purpose of the present study is to provide a more scientifically defensible and fair examination of the relative value of specific abilities and different operationalizations of general cognitive ability in predicting job performance. The present study will evaluate the contribution of *g* and *s* using a construct-oriented approach that logically and theoretically links psychologically interpretable specific abilities with job performance criteria. Moreover, theoretical predictor and criterion relationships will be established at the individual job level instead of using the "broadside" approach common to validity generalization studies. The present study will compare a priori construct-oriented specific abilities to general cognitive ability operationalized as both psychometric *g* and as the combination of primary content areas (verbal and quantitative reasoning) thought to produce an efficient estimate of *g* (Hunter, 1986; Schmidt, 2002; Schmidt & Hunter, 2004).

It is important to examine both methods of estimating general cognitive ability because the construct is not commonly operationalized as psychometric *g* in personnel selection situations. Doing so would require a broad spectrum of ability measures not commonly collected outside of research settings. Most tests used for personnel selection purposes, such as the Wonderlic Personnel Test, are short measures of general cognitive ability that cover a limited area of ability content (Anastasi, 1982). The WPT contains primarily verbal and quantitative reasoning content, with one or two items (out of 50) that can be considered spatial content. Likewise, the Unites States Military operationalizes general cognitive ability using the Armed Forces Qualification Test (AFQT), which is the combination of verbal and quantitative content scales from the ASVAB (Oppler, McCloy, Peterson, Russell, & Campbell, 2001). It is possible that reliance on content specific estimates of general cognitive ability (i.e. verbal and quantitative) may produce a measure of more representative of acculturated learning rather than a representation of the more common conceptualization of *g* (Roberts, Goff, Anjoul, Kyllonen, Pallier, & Stankov 2001).

Job performance criteria

The present study will examine the validity of using general cognitive ability and job related specific ability composites to predict both work sample and overall job performance criterion measures. A critical difference between the work sample and peer/supervisor rating criteria is the scope of the criterion domain measured by each. Borman and Motowidlo (1993) distinguish between task and contextual components of job performance. Task performance is characterized by activities that directly or indirectly contribute to the technical core of the organization. That is, task performance consists primarily of physical or intellectual activities or behaviors typically measured by job analyses and often found in formal job descriptions. The activities that comprise task performance vary from job to job and are often the primary means for distinguishing jobs from one another. Moreover, task performance is thought to be determined by individual differences in knowledge, skills and abilities relevant to appropriate task proficiencies.

Contextual performance is characterized by activities or behaviors that contribute to the effectiveness of the organization but are not part of the technical core. Activities that comprise contextual performance are unlikely to be part of a formal job description and include contributing to the organization through means such as motivation, enthusiasm, cooperation and volunteering. Contextual performance is thought to be common across jobs and primarily determined by non-cognitive variables. Empirical evidence exists to support the claim that task performance is better predicted by knowledge, skills and abilities and contextual performance is better predicted by personality variables (Borman & Motowidlo, 1997; Johnson, 2001; Motowidlo & Van Scotter, 1994)

Because work sample measures are defined by hands on, job specific task proficiency, this operationalization of job performance is likely to be almost completely comprised of task performance. Peer/supervisor ratings of overall performance likewise represent both task and contextual dimensions of job performance. Empirical evidence suggests that supervisors consider task and contextual performance in roughly equal proportion in making overall performance ratings (Borman & Motowidlo, 1997). In corroboration, Johnson (2001) calculated the relative weights of the contribution of task and contextual performance dimensions to supervisor ratings of overall performance across 8 job families and found them to be of similar magnitude (mean of 15.6% and 13.3%, respectively).

The construct-oriented approach in the present context is likely to be most effective when objective measures of job performance are the criterion. Because work samples exclusively represent task performance, they will likely have a stronger relationship with the cognitive predictor variables. Additionally, objective measures of job performance are defined by job related task behaviors specific to a particular job. Establishing logical and theoretical predictor-criterion relationships can be facilitated when both predictor and criterion are defined in terms specific to each individual job (Prediger, 1989).

Hypothesis 1a

Specific ability predictor composites that are logically and theoretically related to each individual job will be superior to psychometric *g* when job performance is operationalized as work sample performance.

Hypothesis 1b

Specific ability predictor composites that are logically and theoretically related to each individual job will be superior to general cognitive ability as measured by the AFQT (i.e. verbal and quantitative ASVAB scales) when job performance is operationalized as work sample performance.

Hypothesis 2a

Specific ability predictor composites that are logically and theoretically related to each individual job will be superior to psychometric *g* when job performance is operationalized as peer/supervisor ratings of overall performance.

Hypothesis 2b

Specific ability predictor composites that are logically and theoretically related to each individual job will be superior to general cognitive ability as measured by the AFQT (i.e. verbal and quantitative ASVAB scales) when job performance is operationalized as peer/supervisor ratings of overall performance.

Research Question

Are sub-group differences on job related specific ability composites lower than those associated with general cognitive ability?

Method

Participants

The sample of participants were drawn from 7,045 individuals in 19 different jobs (Military Occupational Specialties) who were part of the Army Selection and Classification Project (Project A; Campbell, 1990). Individuals from “batch A” were used for the present study. The 4,039 individuals in 9 different jobs from batch A have more extensive (i.e. both objective work samples and subjective peer/supervisor ratings) criterion data and are thus better suited for the present study. Table 1 contains a listing of the sample size for each of the 9 jobs in batch A. The batch A sample is 86.8% male, 72.5% white, 21% black, 2.9% Hispanic and 3.6% “other.” Participant’s ages range from 18 to 37 and most (92%) were under the age of 25 at the time of testing.

Cognitive Measures

A listing of cognitive predictor variables available in the Project A database is found in Table 2. Standardized scale scores from the ASVAB are available for all individuals in the sample. The ASVAB is a 334 item test divided into ten sub-scales (listed in Table 2) that serves as the primary selection and classification test for entry level personnel in the United States military. The numerical operations and coding speed sub-scales are speeded and the remaining sub-scales are power tests. The average internal consistency of the ten sub-scales is .86 (Russell, Peterson, Rosse, Toquam, McHenry, & Houston, 2001). Reliability estimates for each individual test are provided in Table 2. The ASVAB was administered to the individuals in the present sample an average of two years prior to collection of criterion measures (McHenry, Hough, Toquam, Hanson, & Ashworth, 1990).

Table 2 also contains additional cognitive predictors that were developed to measure cognitive constructs conceptually and empirically independent from those measured by the ASVAB. These additional predictors measure spatial, psychomotor and perceptual abilities. Reliability estimates for each scale are provided in Table 2 and represent split-half reliabilities corrected for test length. A correlation matrix of all predictor variables can be found in Table 3.

Specific Abilities

For the purpose of establishing operationalizations of specific abilities that represent psychologically interpretable constructs, the specific ability measures listed in Table 2 were independently identified as indicators of construct level abilities by the author and a doctoral level I-O psychologist using Fleishman's taxonomy of human abilities (Fleishman, 1975; Fleishman & Quaintance, 1984) and the content descriptions of the ability measures. Fleishman and Reilly (1992) provide conceptual definitions and representative tasks and test examples that characterize each ability. For example, "written comprehension" is defined as

> …the ability to understand written sentences and paragraphs. This ability involves reading and understanding the meaning of words, phrases, sentences and paragraphs. It involves reading; it does not involve writing, listening to, or understanding spoken information (pg.8).

Test examples for the written comprehension ability include those that present individuals with sentences or paragraphs of information and ask them to respond to multiple-choice items about that information. Other tests simply ask individuals to identify the meaning of words through definitions, synonyms or antonyms. The word knowledge and paragraph comprehension scales of the ASVAB were therefore used to operationalize the written comprehension construct. Descriptions of the ASVAB sub-tests and Project A cognitive predictors are presented as described by the test developers (Peterson, Hough, Dunnette, Rosse, Houston, Toquam, & Wing, 1990; U.S. MEPCOM, 2002) in Appendix A. Conceptual descriptions of Fleishman's abilities used in the present study can be found in Appendix B. The author and other psychologist agreed on 91% on the measure-to-construct mappings and came to mutual agreement on discrepancies through discussion. A complete list of the measure-to-construct mapping is found in Table 2. A small number of measures did not fit well into Fleishman's taxonomy and are better conceptualized as measures of knowledge rather than ability. For example the auto-shop scale from the ASVAB is described as testing content covered in most high school auto and shop courses such as automotive components and tools and thus is better represented as a measure of knowledge rather than ability.

General Cognitive Ability

General cognitive ability was operationalized in three different ways. Psychometric g was estimated as the factor score from the first principle component extracted from all cognitive measures in Table 2. Ree and Earles (1991b) have demonstrated that factor scores derived from varying extraction methods are equivalent for the purpose of computing factor scores and advocate the principle component model because of its simplicity (Ree et al. 1994). General cognitive ability was also estimated as the AFQT, which is a unit weighted sum of the word knowledge, paragraph comprehension, arithmetic reasoning and math knowledge scales from the ASVAB. This operationalization of general cognitive ability is more representative of how the construct is measured in typical personnel selection settings. The third method of estimating general cognitive ability was to operationalize psychometric *g* as the factor score on the first principle component extracted from the cognitive measures in Table 2, excluding the measures that comprise the specific ability constructs determined to job related for each of the nine jobs under consideration. This required independent estimation of psychometric *g* for each of the samples that make up the nine jobs. Because psychometric *g* is the distillate or communality of cognitive measures, theoretically its estimation should not depend on specific content. The purpose of the third estimation of psychometric g was to eliminate the strict linear dependency of psychometric *g* and operationalizations of specific abilities.

Table 3 contains the correlations among all predictor variables used in the analyses across the nine jobs. Table 3 reveals that the correlations between individual specific ability measures and psychometric *g* are moderate to strong in magnitude. This is a necessary outcome given the principle component methodology of estimating general cognitive ability (Mulaik, 1994). Correlations between individual specific ability measures and the AFQT are also moderate to strong in magnitude, but are generally weaker than the correlations with psychometric *g*. The overall pattern of correlations reveals moderate levels of colinearity among the ASVAB scales. Moreover, the degree of colinearity with the ASVAB is substantially lessened towards the bottom and middle of the matrix. This suggests that efforts to measure constructs independent of the ASVAB were largely successful. Correlations among the measures designed to be independent from the ASVAB are also relatively small.

Criterion Measures

Job performance was operationalized in a number of ways in order for the results to be comparable to prior research that has compared the predictive validity of general cognitive ability and specific abilities (McHenry, et al., 1990; Olea & Ree, 1994; Ree & Earles, 1991a; Ree, et al., 1994). Work sample tests of job performance served as the primary measure of task performance. These “hands on” criterion measures were developed using a comprehensive job analysis (Campbell, Ford, Rumsey, Pulakos, Borman, Felker, De Vera, & Riegelhaupt, 1990).

Hands on measures of job performance consisted of 15 job specific tasks deemed most important for success in a particular job by subject matter experts (SME's). Each of the 15 tasks was composed of a number of steps scored as "go" or "no go." For example, Motor Transport Operators were instructed to perform the task of driving a truck through a road course. Steps in this task include shifting gears without grinding and passing a serpentine roadway without striking barriers. Each task was then scored in terms of percentage of steps correctly performed.

The second measure of job performance was comprised of job knowledge tests specifically designed for each job. Although job knowledge is a questionable operationalization of job performance, it was included for the purpose of making comparisons to prior research. Job knowledge tests were in multiple choice format and designed to measure procedural knowledge specific to each job. Distracter or incorrect item responses were based on common performance mistakes identified by subject matter experts (Knapp, Campbell, Borman, Pulakos, & Hanson, 2001). Job knowledge and work sample measures were also combined to form what has been referred to in prior research as "core technical proficiency" (McHenry, et al 1990; Campbell, Hanson, & Oppler, 2001). Core technical proficiency is equivalent to Borman and Motowidlo's (1993) conceptualization of task performance.

The last operationalization of job performance was comprised of peer and supervisor combined ratings of performance. The purpose of this composite was to represent both task and contextual aspects of job performance. This composite of overall performance is similar to prior composites formed in the analysis of Project A data (McHenry, et al 1990; Campbell, Hanson, & Oppler, 2001). The overall performance composite was formed as the unit weighted combination of three components. The first component was an "army wide" peer/supervisor rating of overall effectiveness. The second component was a job specific peer/supervisor rating of overall effectiveness. The third component was comprised of the sub-components of peer/supervisor ratings of effort, leadership, technical skill, integrity, non-commissioned officer potential and administrative records of promotion rate.

Table 4 contains the correlations among the criterion variables (and general cognitive ability) used in the present analyses across all jobs. The pattern of correlations reveals that overall ratings of performance tend to be moderately to strongly related to ratings of effort, leadership, technical skill and integrity. Both measures of general cognitive ability have the strongest relationship with job knowledge and core technical proficiency (which contains job knowledge). General cognitive ability also has a fairly weak relationship with overall performance ratings and the overall performance composite.

SME Ratings of Predictor-Criterion Relationships

Theoretical links between predictor and criterion measures necessary to implement the construct-oriented approach were established using subject matter expert ratings of the importance of specific abilities to job-performance in each job. SME's were fourteen I-O psychology or management graduate students who had completed an Industrial Psychology course covering topics in personnel selection and one Army ROTC instructor. An example rating measure is included in Appendix B. SME's were presented with a summary description the job for which the rating is being done. For example, the measure presented in Appendix B contains an overview of the job of administrative specialist as well as a number of common tasks often required of administrative specialists. This job description is followed on the next page by a brief conceptual description a specific ability construct. The first ability described in Appendix B is written comprehension. Immediately following the ability description is an item that asks the SME to rate the importance of written comprehension to job performance for the job of administrative specialist using the 5-point scale provided. SME are then presented with a second conceptual definition of an ability construct and asked to rate the importance of that ability to performance of the job of administrative specialist. This continues until the SME's have rated the importance of all seventeen constructs to performance of the job of administrative specialist. This measure was duplicated for the remaining eight jobs under consideration.

SME Rater Training

Prior to completing ratings, all fourteen SME's took part in a group training session familiarizing them with the rating task. A secondary purpose of the practice ratings was aid in the identification and remediation of idiosyncratic raters. SME's were familiarized with the ability construct definitions in order to establish a common understanding of their meaning and distinction from other constructs. In an effort to establish a common frame of reference (Bernardin & Buckley, 1981) and a normative rationale for using the rating scale, SME's were asked to complete practice ratings on two jobs not included in the nine jobs part of the formal analyses. The practice ratings were completed on a measure identical to the one in Appendix B for the jobs of "human resource specialist" and "fire support specialist." In the practice ratings only, SME's were asked to provide a brief rationale for why they assigned each rating. After SME's rated all constructs on the first practice job, their ratings were compiled and examined for agreement. When disagreement was apparent, SME's were lead through a discussion as to potential reasons for a lack on consensus on the construct-to-job rating. This discussion was mainly focused on SME's explaining their rationale for providing ratings to the other raters. The primary reason for disagreement was the result of different interpretations of the job descriptions. Two SME's who had careers in the military (one ROTC instructor and one Army reservist) provided additional insight into the job descriptions and tasks common to the job. This process was then repeated second practice job.

The final part of the training session involved presenting SME's with explanations of the nine jobs included in the formal analyses in order to establish a common understanding of the job descriptions. The two SME's who had careers in the military assisted in the explanation of job descriptions and answered a number of questions regarding military language potentially unfamiliar to civilian SME's. SME's completed the ratings on their own time and all returned their ratings within two weeks of training.

Results

Multiple regression analysis was used to evaluate predictor-criterion relationships. Criterion measures were regressed on the three operationalizations of general cognitive ability as well as the job related specific ability predictors for each job. The number of specific abilities defined as job related depended on the job. Rather than imposing an arbitrary number of predictors in the construct oriented composite, it seemed more reasonable to look for meaningful breaks in the ratings of ability-job performance ratings. The decision rule regarding the job related abilities involved both the average rating of the constructs importance to performing the job and the level of agreement of this rating. Agreement was assessing using James, Demaree and Wolf's (1984) R_{wg} index of inter-rater agreement.

A specific ability was deemed job related and included in the regression model for a particular job if its average rating was greater than or equal to 4 (i.e. "very important" on the 5-point scale) and if raters exhibited at least moderate (i.e. $R_{wg} \geq .50$) agreement. The majority of the ability constructs determined to be job related well exceeded the minimum R_{wg} criterion of .50. Nevertheless, agreement on some ability constructs deemed job related was in the lower bound of what would be considered acceptable agreement. The minimum of .50 was used because of the relatively small number of raters and the sensitivity of R_{wg} to a small number of idiosyncratic ratings.

Model superiority was evaluated by the squared multiple correlation value corrected for cross validation. Both empirical (Cotter & Raju, 1982) and simulation (Drasgow, Dorans, & Tucker, 1979) studies have found that formula-based estimates of cross validity squared multiple correlations are equivalent to estimates obtained using a true cross validation procedure. The second method used to evaluate model superiority was the predicted residual sum of squares value (PRESS) that represents “leave one out” cross validation. That is, instead of splitting the sample in half as in a conventional cross validation procedure, PRESS is equivalent to iteratively predicting each observation’s criterion score using a regression equation estimated from all remaining observations. The PRESS statistic represents the sum of prediction errors and thus the model with the lowest residual value is preferred. Corrected R^2 and the PRESS statistic were used in favor of a conventional cross validation procedure because of the cumbersome nature of the computations necessary to cross validate factor scores (i.e. psychometric *g*). Cotter and Raju (1982) endorse the use of corrected cross validity estimates and factor scores in multiple regression analysis.

Subject Matter Expert Ratings of Job Related Abilities

SME’s average ratings and agreement levels for each of the nine jobs are presented in Table 5. One SME (for whom English was a second language) was deemed an idiosyncratic rater across all jobs and removed from the agreement analysis entirely. Another rater filled the questionnaire out improperly and was also removed from the analysis entirely. A small number (≥ 2) of raters were removed from the agreement and rating analysis for each job based on the inference that these raters had a poor understanding of the job description. These raters were not necessarily the same for each job. This selective removal was necessary because of the sensitivity of R_{wg} to idiosyncratic ratings with a small number of raters. For example, a rater who rated “electrical information” as not important to the job of radio operator was assumed to have a poor understanding of that job because of the explicit mention of the need to repair, maintain and test electrical equipment in the job description. The removal of this rater resulted in R_{wg} for the electrical information rating changing from .33 to .87.

Table 5 indicates how many raters (out of 12 with interpretable data) were used in the computation of the average ratings and agreement indices. The italicized ability constructs in Table 5 are those that comprised the composite of job related specific abilities included in the job specific regression equations. For example, the italicized ability constructs "reaction time," "multi-limb coordination," "response orientation," "spatial orientation" and "control precision" were deemed job related to infantrymen by virtue of their high average rating of importance and at least moderate agreement. For infantrymen, the regression equation of job related specific abilities was comprised of the eight measures that represent the five ability constructs determined to be job related. Table 5 indicates how many predictor variables (*k*) comprise the composite of job related specific abilities for each job. The number of ability constructs that comprise the job related composite is not equal to the number of ability measures (*k*) because some constructs are represented by more than one measure (e.g. simple reaction time is represented by a time variable and a percent correct variable). The decision rule based on an average rating of greater than or equal to 4 and at least moderate agreement was violated for the military police job. An exception was made for this job because of the conceptual similarity between the reaction time (for which there was acceptable agreement and an average rating of nearly 4) and response orientation (which had a high average rating but low agreement) constructs.

General cognitive ability vs. specific abilities

Table 6 presents the correlations between the three operationalizations of general cognitive ability and the criterion measures as well as the multiple correlations between regression weighted job related specific ability composites and the criterion measures. The correlations and multiple correlations in Table 6 have *not* been corrected for cross validation. The average correlation between psychometric *g* estimated from all cognitive predictors and psychometric *g* estimated from all predictors but those included in the job related specific ability composite is near unity (*r* = .98). It is therefore reasonable to conclude that the estimation of general cognitive ability was almost completely unaffected by the inclusion or removal of content specific measures. In light of this finding, comparisons between job related specific ability composites and psychometric *g* will be made using the operationalization estimated to eliminate the strict linear dependency (i.e. g_3 in Tables 6, 7 and 8). All references to psychometric g from this point forward refer to the third operationalization of general cognitive ability (g_3) unless otherwise noted. It is also worth noting that although the correlation between psychometric g and the AFQT is high (.78), the common variance between them is just over 60% and thus cannot be considered isomorphic.

Table 6 reveals that across all job, both general cognitive ability and the job related specific ability composites have the strongest relationship with job knowledge and the weakest relationship with the overall performance composite. The second to last column in Table 6 contains the incremental variance psychometric g adds to a model that contains the job related specific ability composite for a particular job. The last column in Table 6 contain the incremental variance the job related specific ability composite adds to a model that contains psychometric g. In both cases, the increment is typically statistically significant but small from a pragmatic perspective. When work sample performance is the criterion, psychometric g adds statistically significant incremental variance beyond the specific ability composite in seven of the nine jobs. For the same criterion measure, the job related specific ability composite adds statistically significant incremental variance in four of the nine jobs. When overall performance is the criterion, psychometric g adds statistically significant incremental variance beyond the specific ability composite in two of the nine jobs and the specific ability composite adds statistically significant incremental variance in four of the nine jobs. Job related specific ability composites therefore provide similar incremental variance across criteria.

Table 7 presents R^2 values that have been corrected with Wherry's (1931) formula for estimating population squared cross validity. When work sample performance is the criterion, the job related specific ability composite explains more variance in job performance (i.e. has a larger corrected R^2 value) than psychometric g in four out of nine jobs. This provides only partial support for hypothesis 1a, which states that the specific ability composites will explain more variance in work sample performance than psychometric *g*. For the same criterion measure, the job related specific ability composite explains more variance in job performance than the AFQT in seven of the nine jobs. This provides stronger (but still only partial) support for hypothesis 1b, which states that the specific ability composites will explain more variance in work sample performance than the AFQT. When overall job performance is the criterion, job related specific ability composites explain more variance in job performance than psychometric *g* in six of the nine jobs. This provides partial support for hypothesis 2a, which states that specific ability composites will explain more variance in overall job performance than psychometric *g*. When overall job performance is the criterion, specific ability composites explain more variance in job performance than the AFQT in seven out of nine jobs. This provides partial support for hypothesis 2b, which states that the specific ability composites will explain more variance in overall job performance than the AFQT.

Although not part of the formal hypotheses, the relationship between the cognitive predictors and measures of job knowledge or operationalizations of job performance that include job knowledge were examined in order to compare results with prior studies. Job related specific ability composites explain more variance in job knowledge than psychometric *g* in only one of the nine jobs. Job related specific ability composites explain more variance in job knowledge than the AFQT in seven of the nine jobs. Job related specific ability composites explain more variance in core technical proficiency than psychometric *g* in only three of the nine jobs. Job related specific ability composites explain more variance in core technical proficiency than the AFQT in seven of the nine jobs.

Table 8 contains PRESS values for the three operationalizations of general cognitive ability and for the job related specific ability composites as predictors of work sample and overall job performance. When work sample performance is the criterion, the job related specific ability composites predict job performance better (i.e. have a smaller residual value) than psychometric g in three of the nine jobs. This is consistent with the corrected squared cross validity results with the exception of the cannon crewmember job, for which psychometric g has a lower PRESS value but explains less variance in work sample job performance. Again, these results provide only partial support for hypothesis 1a. The job related specific ability composites provide superior prediction of work sample job performance compared to the AFQT in seven of the nine jobs. The PRESS values are consistent with the corrected squared cross validity coefficients and provide partial support for hypothesis 1b.

When overall job performance is the criterion, the job related specific ability composites are superior to psychometric g in the prediction of job performance in four out of the nine jobs. The PRESS values are consistent with the corrected squared cross validity coefficients with the exception of the cannon crewmember and tank crewmember jobs, for which the job related specific ability composites explain more variance in overall job performance than psychometric g but have higher total residual values. This provides partial support for hypothesis 2a. The job related specific ability composites are superior to the AFQT in predicting overall job performance in five of the nine jobs. The PRESS values are consistent with the corrected squared cross validity coefficients with the exception of the cannon crewmember and tank crewmember jobs, for which the job related specific ability composites explain more variance in overall job performance than the AFQT but have higher total residual values. This provides partial support for hypothesis 2b.

The disparity between the corrected squared cross validity coefficients and the PRESS values is likely to be related to the number of predictors in the regression models. That is, psychometric *g* and the AFQT are represented by a single predictor variable and the job related specific ability composites are comprised of anywhere between two and fourteen predictor variables. Although increasing the number of predictor variables will often lead to more explained variance in the criterion, doing so may not necessarily add practically or meaningfully significant increments and is less parsimonious. Inconsistencies between the PRESS values and corrected squared cross validity coefficients arise for the two jobs that have the largest number of predictor variables in their job related specific ability composite (i.e. cannon crewmember and tank crewmember).

Convergent and discriminant validity of job related specific ability composites

Because of the colinearity traditionally found in cognitive predictor variables, it is important to establish that the predictive validity of the job related specific ability composites is indeed due to job relatedness and/or job specificity. The job related specific ability composite for each job was used to predict work sample and overall job performance in every other job. For example, the infantry composite was used to predict job performance for infantrymen and also for mechanics, administrative specialists, motor transport operators etc.

The results of this analysis are presented in Table 9. The diagonals in these matrices represent the multiple correlation of the job related specific ability composite predicting job performance (operationalized as either work sample performance or overall performance) in the job it is logically and theoretically related to. Thus, if the predictive validity is indeed due to the job specificity of the predictor constructs the diagonals should have the highest multiple correlation values and the off diagonals should have relatively lower values. As Table 9 indicates, there is very little convergent or discriminant validity in the job related specific ability composites as predictors of work sample or overall job performance. That is, it is often the case that a job related specific ability composite is a better (or approximately equivalent) predictor of job performance in a job other than the one it is designed to predict and also often the case that the job related specific ability composite is not the best predictor of the job it was designed to predict. For example, the cannon crewmember composite has a stronger relationship with motor transport operator work sample performance than it does with cannon crewmember work sample performance. Furthermore, the tank crewmember composite has a substantially stronger relationship with administrative specialist work sample performance than the administrative specialist composite does. Although the diagonal values are generally high, they are not necessarily the highest in their respective matrix and the off diagonal values are not low or even necessarily lower than the diagonal values. Table 10 is analogous to Table 9, but instead presents incremental variance beyond psychometric *g* explained by the job related specific ability composites. Incremental variance was examined in addition to validity coefficients because of the possibility of differential *g* loading across jobs.

The matrices in Table 9 and Table 10 largely undermine the partial support for hypotheses 1 and 2. Similar jobs with similar composites demarcated by the dotted boxes in

Tables 9 and 10. Discriminant validity would not be expected within these boxes. Although some overlap among the job related specific ability composites might be expected (especially in combat related jobs), the lack of convergent and discriminant validity even extends into jobs that are extremely different (e.g. tank crewman and administrative specialist). This is compounded by the fact that this finding is apparent even when job performance is operationalized as job specific work samples because both the predictors and criterion are theoretically job specific.

Sub-group differences

Table 11 contains standardized black-white differences (d-scores) on general cognitive ability and individual specific ability measures across all jobs. Differences on specific ability measures (in favor of whites) range from very small (.03) in many of the time tests to fairly large (1.31) in the ASVAB auto-shop scale. Black-white differences in all specific ability measures are smaller than differences in psychometric *g* (1.59) and many are smaller than differences in the AFQT (.98). Table 12 presents the standardized black-white difference in *predicted* work sample and overall performance scores for psychometric g, the AFQT and the job related specific ability composites (in which job related specific ability measures are regression weighted). The last column in Table 12 contains actual black-white standardized differences on work sample and overall performance criterion measures. Psychometric *g* produces a difference of 1.59 standard deviation units and the AFQT produces a difference of approximately one standard deviation in favor of whites. D-scores for the job related specific ability composites range from .46 to 1.47 across work sample and overall job performance scores. The difference between blacks and whites is generally smaller for predicted overall performance scores than it is for predicted work sample scores. The composites that explain more variance in job performance are to some extent those that have larger sub-group differences. The correlation between the job related specific ability composite d-scores and corrected squared cross validity coefficient is .53 ($p<.02$).

When work sample performance is the criterion, the job related specific ability composites explain more variance in job performance than psychometric *g* in only four out of nine jobs but would also produce smaller sub-group differences than psychometric *g* in all nine jobs. The job related specific ability composites explain more variance in work sample job performance than the AFQT in seven out of nine jobs but would also produce larger sub group differences than the AFQT in five out of nine jobs. Thus, for two jobs (medical specialist and military police) the regression weighted job related specific ability composites would explain more variance in job performance than the AFQT and produce smaller sub-group differences.

When overall job performance is the criterion, job related specific ability composites explain more variance in job performance than psychometric *g* in six of the nine jobs and would produce smaller sub-group differences in all nine jobs. Job related specific ability composites explain more variance in overall job performance than the AFQT in seven out of nine jobs but would produce larger sub-group differences in five of the jobs. Thus, for two jobs (motor transport operator and military police) the regression weighted job related specific ability composites would explain more variance in job performance than the AFQT and produce smaller sub-group differences.

Table 12 indicates that d-scores associated with predicted criterion performance are often substantially larger than d-scores on actual criterion scores. Psychometric g produced a predicted work sample score with a standardized black-white difference three times larger than the actual difference and a predicted overall performance score with a standardized black-white difference over ten times larger than the actual difference. The AFQT produced a predicted work sample score with a standardized black-white difference nearly twice as large as the actual difference and a predicted overall performance score with a standardized black-white difference over six times larger than the actual difference. The job related specific ability composites also produced predicted work sample and overall job performance scores larger than actual scores, but with the exception of cannon crewmember (work sample performance) and motor transport operator (overall performance) the ratio of predicted to actual performance is smaller than that associated with psychometric *g*. Job related specific ability composites generally produced a larger ratio of predicted to actual performance than the AFQT for work sample criteria and generally produced a smaller ratio or predicted to actual performance for overall performance criteria.

Discussion

One of the primary purposes of the present study was to attempt to reconcile the seemingly overwhelming body of empirical evidence arguing for the preeminence of general cognitive ability in relation to specific abilities (Carretta & Ree, 2000; Hunter & Hunter, 1984; Jones & Ree, 1998; McHenry et al., 1990; Olea & Ree, 1994; Ree & Earles, 1991; Ree et al. 1994; Schmidt & Hunter, 1998; Schmidt, 2002) with the general resistance of the majority of Industrial-Organizational psychologists to such a position (Murphy et al., 2003). Despite the body of literature that suggests the contrary, the majority of SIOP members surveyed by Murphy et al., (2003) believe that different jobs require different cognitive abilities. Moreover, only a quarter of SIOP members believe that a combination of specific abilities has little advantage over general cognitive ability and less than a quarter believe that any combination of specific ability measures is actually a measure of *g*.

Although the reasons for many SIOP members resistance to primacy of general cognitive ability are not apparent from the Murphy et al. (2003) survey, one likely reason for the general vs. specific controversy is that the “g-centric” viewpoint is at odds with classic models of personnel selection. That is, the traditional personnel selection paradigm begins with a job analysis for the purpose of identifying knowledge, skills, abilities and others (KSAO’s) relevant and important to the job. The inherent assumption in this process is that the KSAO’s relevant to a particular job depend on performance requirements of that job. Furthermore, it is implicit in this model that there is variance in these performance requirements and thus variance in which KSAO’s are important to each job (Gatewood & Feild, 2001). The selection model just described is more compatible with the notion that factorial complexity in prediction should be obtained by regression weighted composites that are theoretically related to the criterion rather than an omnibus predictor (Nunally, 1978). This is consistent with the majority view in the SIOP member survey that different jobs require different cognitive abilities. Related to SIOP member's belief is the reality that a g-centric selection paradigm is generally unacceptable to managers in private business regardless of the empirical evidence (Tenopyr, 2002). The view that specific abilities are irrelevant in relation to general cognitive ability invalidates the traditional selection paradigm because it suggests that different jobs do not require different ability profiles (Schmidt, 2002).

Another related reason for this disparity between research and opinion is that although there is a rather large quantity of research to suggest the primacy of general cognitive ability in personnel selection, the quality of this research as well as its theoretical foundation is often called into question (Landy & Shankster, 1994; Murphy, 1996). The conceptualization and measurement of cognitive abilities has been relatively stagnant since Spearman's (1904) original work. As a result, the general vs. specific ability controversy has been largely based on utility rather than understanding. The principle component model implemented in the studies conducted by Ree and colleagues is a prime example of utility taking precedent over scientific understanding.

The contention of the present study was that the primary evidence used to support the view that specific abilities are of little importance relative to general cognitive ability did not faithfully represent this classic selection model and was based on tenuous assumptions about the operationalizations of general and specific cognitive abilities. That is, these studies approached the issue from a data driven perspective that defined specific abilities in a fairly dismissive mathematical manner rather than in psychologically interpretable terms (Olea & Ree, 1994; Ree & Earles, 1991; Ree et al. 1994). By virtue of being defined in un-interpretable terms with respect to content or function, prior operationalizations of specific abilities did not lend themselves to logical and theoretical relationships with job specific job performance. The general thesis of the present study was that if a construct oriented approach that is largely based on this classic selection model (Hollenbeck & Whitener, 1988; Schnieder, et al., 1996) were implemented, a composite of psychologically interpretable job related specific abilities might prove equivalent or even superior to general cognitive ability in the prediction of job performance.

In support of the general contention of the present study, squared validity coefficients (corrected for cross validation) in Table 7 reveal that regression weighted job related specific ability composites explain substantially more variance in both task and overall job performance than the summation of verbal and quantitative content scales (i.e. the AFQT) for almost every job analyzed. This is significant from a pragmatic perspective because it demonstrates that the adoption of a construct oriented approach can be superior to the most common way of estimating general cognitive ability in applied personnel selection situations.

Although the results of this study suggest that job related specific ability composites are superior predictors of job performance in some instances and general cognitive ability is superior to specific ability composites in others, the overall pattern of predictor-criterion relationships suggests that differences between the predictive validity of general cognitive ability and job related specific ability composites are small. This is in stark contrast to the conclusion of other studies that have addressed the same issue (Carretta & Ree, 2000; Jones & Ree, 1998; Olea & Ree, 1994; Ree & Earles, 1991; Ree et al. 1994); which has been that specific abilities explain little to no variance in job performance. The difference between the present study and prior studies is how specific abilities have been operationalized. Ree and colleagues defined general cognitive ability as the first principle component extracted from a multi-aptitude test and specific abilities as that which is orthogonal to general cognitive ability. The assumption that specific abilities are orthogonal to general cognitive ability is tenuous because almost all models of cognitive abilities recognize the interrelatedness and interdependency between general cognitive ability and specific abilities. That is, there is no one single or pure measure of general cognitive ability because psychometric *g* is the distillate or communality of specific ability measures (Jensen, 2002; Murphy, 1996). In order to be more consistent with theoretical models of cognitive abilities, the present study defined specific abilities according to content and function of the ability measures.

Despite the attempt of the present study to overcome many of the conceptual and methodological limitations of prior research concerned with the general vs. specific ability controversy, the overall pattern of results do not support conclusions radically divergent from prior work. The results suggest the equivalence or superiority of adopting a construct oriented approach to exclusive use of general cognitive ability, but the convergent-discriminant validity matrices in Table 9 make it difficult to argue that the findings of the present study are convincing evidence against the relative preeminence of general cognitive ability (operationalized as psychometric *g*) as a predictor of job performance. Although it is certain that the job related specific ability composites in the present study are imperfect with regard to their accuracy and job relatedness, the apparent lack of discriminant validity suggests that the specificity of the composites is not the primary driving force behind their predictive validity.

Congruence with prior empirical work

One of the most striking results of the present study is the relatively small amount of variance general cognitive ability and job related specific ability composites explain in job performance criterion measures that do not include job knowledge. Using essentially the same data as in the present study, McHenry et al. (1990) report a multiple correlation (corrected for range restriction and adjusted for shrinkage) between general cognitive ability and “core technical proficiency” or task performance across all jobs of .63. Table 4 indicates that the uncorrected correlation between psychometric g, work sample performance (task performance) and overall performance (task and contextual performance) is .32 and .14, respectively. The critical difference, aside from the correction and adjustment, is that McHenry et al’s (1990) operationalization of job performance includes job knowledge. Table 6 indicates that the un-corrected correlations between cognitive predictors and job knowledge measures are similar in magnitude to those found by McHenry et al and substantially stronger than they are with measures of work sample or overall performance.

In another analysis of Project A data, Oppler et al. (2001) were able to obtain corrected multiple correlations ranging from .66 to .85 (depending on the job) between task performance (core technical proficiency) and a battery of 28 regression weighted cognitive and personality predictors. Moreover, they were able to obtain multiple correlation values only slightly smaller than values obtained using all predictors by using a reduced set of variables based on SME’s judgment of predictors (≥ 10 cognitive or non cognitive predictors) likely to maximize prediction in each job. The analyses conducted by Oppler et al (2001) provided impetus for the rationale behind the present study because one of the findings was that the regression weights for ability predictors varied depending on the job. That is, Oppler et al’s results reveal that the most predictive specific ability measures are not the same across jobs and suggest that there is value in tailoring ability composites to match job requirements.

The argument has been made that job knowledge is a legitimate performance criterion in the military because it is an index of “readiness” (Knapp et al. 2001). Nevertheless, studies done in military samples are often cited as generalizable to non-military populations. If we must accept that measures of specific abilities contain a large percentage of variance due to general cognitive ability, then we must also accept that measures of job knowledge are subject to a similar argument. That is, it is reasonable to suspect that there is quite a bit of similarity and common method variance between measures of job knowledge and measures of KSA’s. As Table 4 indicates, the relationship between general cognitive ability and job knowledge is substantially stronger (r =.55) than it is with any other criterion measure. Job knowledge should be at best viewed as a mediator between cognitive ability and job performance (Hunter, 1986), but because it has much more in common with predictors variables it is not reasonable for it to be a stand alone measure or part of a job performance composite.

The magnitude of relationships between cognitive predictors and job performance in the present study are more comparable to those found in Ree et al. (1994), who used hands on work sample performance, interview work sample performance and their combination as criterion measures. Ree et al (1994) report correlations (corrected for range restriction) between *g* and job performance as high as .75, but uncorrected correlations did not exceed .34. Although the approach adopted by Ree et al for operationalizing general and specific abilities is superior from a utilitarian perspective in which validity is the only concern, one notable difference is that the job related specific ability composites in the present study were generally able to maintain almost all of the predictive validity of psychometric *g* but produced lower (albeit often still large) black-white differences. Although colinearity makes it difficult to be sure, one possible explanation for this finding is that there is variance due to specific abilities that is responsible for the predictive validity of the job related composites. In absolute terms, psychometric *g* is generally the superior predictor of job performance, but also produces the largest black-white differences. Based on Table 9, it appears that the job related specific ability composites also contain a great deal of variance that cannot be interpreted as distinct from the general factor, but also presumably contain some job related variance not due to *g*. That is, psychometric *g* is arguably the best and purest measure of general cognitive ability but also produces the largest black-white differences. The job related specific ability composites viewed as proxies of *g* also contain some "impurities" (i.e. non-*g* specific ability variance) that are still job related but do not exhibit sub-group differences to the extent of psychometric *g*. Black-white differences produced by specific ability composites are more consistent with differences found in job performance measures than those produced by psychometric *g*.

There is no disputing the fact that general cognitive ability is the best single predictor of job performance. Nevertheless, the role of *g* in personnel selection remains a contentious topic because of the social issues surrounding cognitive ability testing (Viswesvaran & Ones, 2002). That is, the use of general cognitive ability in personnel selection makes it difficult to balance the goal of a valid and efficient selection system with other valuable organizational goals such as social equity and diversity (Murphy, 2002; Outtz, 2002). The use of measures with smaller sub-group differences (personality) in lieu of cognitive ability would be deleterious to any selection paradigm because of the consequential under-representation of individuals likely to be high task performers (Kehoe, 2002). Organizations are thus faced with a seemingly intractable balancing act between efficiency and social responsibility.

Complicating the issue further is the finding that sub-group differences on general cognitive ability are typically larger than those on measures of job performance (Hattrup, Rock,

& Scalia, 1997; Rotundo & Sackett, 1999). Table 12 indicates that black-white differences on cognitive measures are generally much larger than differences found in measures of job performance in the present study. Outtz (2002) interprets discrepancies such as this to mean that measures of general cognitive ability capture variance unrelated to job performance or that individuals can compensate for general cognitive ability on the job. He also notes that the disparity between differences on general cognitive ability measures and differences on job performance often results in more false negatives for minorities.

The construct oriented approach implemented in the present study does not eliminate sub-group differences or the imbalance between racial differences on predictor and criterion scores. The construct oriented approach does, however, alleviate some of this inequity by producing smaller sub-group differences than psychometric *g* and generally demonstrating a smaller ratio of predicted to actual performance. This is accomplished without substantial loss of predictive validity. The approach implemented in the present study appears to be superior from the perspective of bridging the gap between validity and social policy.

Limitations of the present study

A primary reason for the lack of discriminant validity of the job related specific ability composites is the apparent difficulty in separating general and specific abilities in a correlational design such that specific abilities are conceptually interpretable yet distinct from *g*. That is, the construct oriented approach depends on linking predictor and criterion measures in a theoretically meaningful manner. Although this has been successful in the realm of personality (Paunonen & Ashton, 2001; Schneider et al. 1996), in which positive manifold also exists (Ones and Viswesvaran 1996), the colinearity among the cognitive variables in the present study is the primary reason for the absence of discriminant validity in found in Table 9. This is to some extent unexpected because even though the colinearity appears fairly strong among the ASVAB scales, the correlations towards the bottom and middle of the matrix in Table 3 exhibit positive manifold to a lesser degree. Moreover, it is the psychomotor and perceptual ability measures represented at the bottom of the matrix that were most often deemed job related in the jobs under consideration.

Perhaps the greatest limitation of the present study lies with the attempt to establish logical and theoretical links between ability constructs and jobs. Although the SME sample is arguably a legitimate pool of experts in the realm of ability constructs and personnel selection, the majority of them did not have expertise in or even much independent knowledge of the jobs under consideration. The topic that consumed much of the SME training surrounded the general lack of familiarity with military work duties involved in many of the jobs. The job descriptions provided a summary overview of the major tasks and responsibilities required to perform each job, but were by no means exhaustive or complete. Even if a more exhaustive and complete description were to be provided, the fact that the majority of the SME's had very little experience with which to identify with military jobs would have been problematic. A number of SME's agreed that the rating task could have been facilitated if they either were more familiar with the jobs or were somehow involved in the job analyses.

Future Research

The lack of discriminant validity found in Table 9 suggests it is unlikely that challenges to the methodology and conclusions of the g-centric view can come from research that relies solely on correlations. Results of the present study as a whole ultimately suggest that there is much more to overcome in this controversy. The positive manifold among the specific measures in Table 2 is readily apparent and indeed troublesome for attempts to operationally distinguish between general and specific abilities. Colinearity makes it difficult to determine which abilities are responsible for performance and thereby masks the potential contribution of specific abilities to job performance (Murphy, 2002). This interrelatedness has been extended by some (e.g. Ree & Carretta, 2002; Schmidt, 2002) to make the argument that measures of specific ability mostly measure general cognitive ability and that the combination of two or more specific ability measures is a de facto measure of general cognitive ability. Nevertheless, it is circular to define the construct of general cognitive ability as being comprised of specific ability measures and then argue that specific abilities are not distinct from general cognitive ability because they are correlated with it. The operationalization of general cognitive ability as the first unrotated principle component guarantees that each individual ability measure will have a moderate to strong relationship with *g* (Mulaik, 1994).

Perhaps the more promising avenue of research in this area is to approach the issue from both a psychometric and experimental perspective rather than relying solely on correlational designs (Landy & Shankster, 1994). The relationship of general and specific abilities with task performance has been examined in an experimental context (Ackerman, 1987; 1988; 1992; Ackerman & Kanfer, 1993), which provides a more complete theoretical perspective on the matter. According to Ackerman's (1988) model, general cognitive ability's relationship with task performance is attenuated over time in tasks that are consistent and can thus be relegated to automatic processing. Moreover, the relationship between specific abilities involved in automatic processing requirements of a consistent task becomes more strongly related to task performance over time. Inconsistent tasks that require more cognitive resources are more dependent on general cognitive ability and content relevant abilities and this dependence is less attenuated over time (Ackerman, 1987). Although much of the empirical work that supports this theoretical model involves simple laboratory tasks such as reaction time, there is evidence to suggest the model applies to complex tasks as well (Ackerman, 1992). Furthermore, the findings involving complex tasks suggest there is value in considering the theoretical relationship between ability predictors and criterion measures and thereby incentive for tailoring predictor batteries to match task requirements.

Conclusion

Results of the present study suggest that job related specific ability composites can predict work sample and overall ratings of job performance about as well as or better than general cognitive ability while at the same time exhibiting smaller sub-group differences than psychometric *g*. The construct oriented approach implemented in the present study has the added benefit of being more consistent with traditional selection paradigms and psychometric theory (Gatewood & Feild, 2001; Nunnally, 1978) in addition to being more palatable to managers in private business (Tenopyr, 2002). Moreover, the use of specific ability composites as opposed to a measure of general cognitive ability has the potential to result in more favorable applicant reactions and to be more legally defensible (Kehoe, 2002).

Implementation of the construct oriented approach in the present study was largely imperfect, but demonstrates potential for the value of this approach with respect to balancing validity and social equity. It is likely that further gains toward the goal of achieving valid and equitable outcomes in personnel selection can be facilitated by considering the content and function of specific ability measures in relation to job requirements. A more rigorous application of the construct oriented approach that includes the use of true SME's in addition to technical and theoretical refinements in the measurement of cognitive abilities has the potential to alleviate some of the contentiousness surrounding cognitive abilities in employment testing.

References

Ackerman, P.L. (1987). Individual differences in skill learning: An integration of psychometric and information processing perspectives. *Psychological Bulletin, 102*, 3-27.

Ackerman, P.L. (1988). Determinants of individual differences during skill acquisition: Cognitive abilities and information processing. *Journal of Experimental Psychology: General, 117*, 288-318.

Ackerman, P.L. (1992). Predicting individual differences in complex skill acquisition: Dynamics of ability determinants. *Journal of Applied Psychology, 77*, 598-614.

Ackerman, P.L. & Kanfer, R. (1993). Integrating laboratory and field study for improving selection: Development of a battery for predicting air traffic controller success. *Journal of Applied Psychology, 78*, 413-432.

Ashton, M.C. (1998). Personality and job performance: The importance of narrow traits. *Journal of Organizational Behavior, 19*, 289-303.

Balzer, W.K. & Sulsky, L.M. (1992). Halo and performance appraisal research: A critical examination. *Journal of Applied Psychology, 77*, 975-985.

Bernardin, H.J. & Buckley, M.R. (1981). Strategies in rater training. *Academy of Management Review, 6*, 205-212.

Borman, W.C. & Motowidlo, S.J. (1993). Expanding the criterion domain to include elements of contextual performance. In N. Schmitt, W.C. Borman & Associates (Eds.) *Personnel Selection in Organizations* (pp. 71-98).San Francisco, CA: Jossey Bass.

Borman, W.C. & Motowidlo, S.J. (1997). Task performance and contextual performance: The meaning for personnel selection research. *Human Performance, 10*, 99-109.

Borsboom, D., Mellenbergh, G.J., & van Heerden, J. (2004). The concept of validity. *Psychological Review, 111*, 1061-1071.

Bowman, D.B., Markham, P.M., & Roberts, R.D. (2002). Expanding the frontier of human cognitive abilities: So much more than (plain) g! *Learning and Individual Differences, 13*, 127-158.

Campbell, C.H., Ford, P., Rumsey, M.G., Pulakos, E.D., Borman, W.C., Felker, D.B., De Vera, M.V. & Riegelhaupt, B.J. (1990). Development of multiple job performance measures in a representative sample of jobs. *Personnel Psychology, 43*, 277-300.

Campbell, J.P. (1990). An overview of the army selection and classification project (Project A). *Personnel Psychology, 43*, 231-239.

Campbell, J.P, Hanson, M.A., & Oppler, S.H. (2001). Modeling Performance in a Population of Jobs. In J.P Campbell & D.J. Knapp (Eds.) *Exploring the Limits in Personnel Selection* (pp. 307-333). Mahwah, NJ: Lawrence Erlbaum.

Carretta, T.R. & Ree, M.J. (2000). General and specific cognitive and psychomotor abilities in personnel selection: The prediction of training and job performance. *International Journal of Selection and Assessment, 8*, 227-236.

Carroll, J.B. (1993). *Human cognitive abilities: A survey of factor analytic studies*. New York, NY: Cambridge University Press.

Ceci, S.J. (2000). So near and yet so far: Lingering questions about the use of general intelligence for college admission and employment screening. *Psychology, Public Policy, and Law, 6*, 233-252.

Cotter, K.L. & Raju, N.S. (1982). An evaluation of formula based population squared cross validity estimates and factor score estimates in prediction. *Educational and Psychological Measurement, 42*, 493-519.

Cronbach, L.J., & Meehl, P.E. (1955). Construct validity in psychological tests. *Psychological Bulletin, 52,* 281-302.

Deary, I.J., Austin, E.J., & Caryl, P.G. (2000). Testing versus understanding human intelligence. *Psychology, Public Policy, and Law, 6*, 180-190.

Drasgow, F., Dorans, N.J., & Tucker, L.R. (1979). Estimators of squared cross validity coefficient: A Monte Carlo investigation. *Applied Psychological Measurement, 3*, 389-399.

Fleishman, E. A. (1975). Toward a taxonomy of human performance. *American Psychologist, 30*, 1127-1140.

Fleishman, E.A. & Mumford, M.D. (1991). Evaluating classifications of job behavior: A construct validation of the ability requirement scales. *Personnel Psychology, 44*, 523-575.

Fleishman, E. A. & Quaintance, M. K. (1984). *Taxonomies of human performance: The description of human tasks.* Orlando, FL. Academic Press.

Fleishman, E. A. & Reilly, M. E. (1992). *Handbook of human abilities: Definitions, measurements, and job task requirements.* Palo Alto, CA. Consulting Psychologists Press.

Garlick, D. (2002). Understanding the nature of the general factor of intelligence: The role of individual differences in neural plasticity as an explanatory mechanism. *Psychological Review, 109*, 116-136.

Gatewood, R.D. & Feild, H.S. (2001). *Human resource selection.* Fort Worth: Harcourt.

Ghiselli, E.E. (1973). The validity of aptitude tests in personnel selection. *Personnel Psychology*, 26, 461-477.

Goldstein, H.W., Zedeck, S. & Goldstein, I.W. (2002). *G*: Is this your final answer? *Human Performance, 15*, 123-142.

Gottfredson, L.S. (1997a). Why g matters: The complexity of everyday life. *Intelligence, 24*, 79-132.

Gottfredson, L.S. (1997b). Mainstream science on intelligence: An editorial with 52 signatories, history and bibliography. *Intelligence, 24*, 13-23.

Gottfredson, L.S. (2002). Where and Why g matters: Not a mystery. *Human Performance, 15*, 25-46.

Gould, S.J. (1996). *The mismeasure of man*. New York: Norton.

Guttman, L. (1992). The irrelevance of factor analysis for the study of group differences. *Multivariate Behavioral Research, 27*, 175-204.

Hattrup, K., Rock, J., & Scalia, C. (1997) The effects of varying conceptualizations of job performance on adverse impact, minority hiring, and predicted performance. *Journal of Applied Psychology, 82*, 656-664.

Hirsh, H.R., Northrop, L.C., & Schmidt, F.L. (1986). Validity generalization results for law enforcement occupations. *Personnel Psychology, 39*, 399-420.

Hogan, J. & Roberts, B.W. (1996). Issues and non-issues in the fidelity-bandwidth trade-off. *Journal of Organizational Behavior, 17*, 627-637.

Holland, J.L. (1985). *Making Vocational Choices*. Englewood Cliffs, NJ: Prentice-Hall.

Hollenbeck, J.R. & Whitener, E.M. (1988). Criterion related validation for small sample contexts: An integrated approach to synthetic validity. *Journal of Applied Psychology, 73*, 536-544.

Horn, J.L. (1986). Remodeling old models of intelligence. In B. B. Wolman (Ed) *Handbook of Intelligence: Theories, Measurement, and Applications* (pp. 267-300). New York: Wiley.

Hunter, J.E. (1986). Cognitive ability, cognitive aptitudes, job knowledge and job performance. *Journal of Vocational Behavior, 29*, 340-362.

Hunter, J. E. & Hunter, R. F. (1984). Validity and utility of alternative predictors of job performance. *Psychological Bulletin, 96*, 72-98.

Jensen, A.R. (2000). Psychometric g: Definition and substantiation. In R.J. Sternberg & E.L. Grigorenko (Eds), *The General Factor of Intelligence: How general is it?* (pp. 39-53). Mahwah, NJ: Lawrence Earlbaum.

Jensen, A. R. & Weng, L. (1994). What is a good g? *Intelligence, 18*, 231-258.

Jensen, A.R. (1980). *Bias in mental testing*. New York: Free Press

Johnson, J.W. (2001). The relative importance of task and contextual performance dimensions to supervisor judgments of overall performance. *Journal of Applied Psychology, 86*, 984-996.

Jones, G.E. & Ree, M.J. (1998). Aptitude test score validity: No moderating effect due to job ability requirement differences. *Educational and Psychological Measurement, 58*, 284-294.

Kehoe, J.F. (2002). General mental ability and selection in private sector organizations: A commentary. *Human Performance, 15 (1/2)*, 97-106.

Knapp, D.J., Campbell, C.H., Borman, W.C., Pulakos, E.D. & Hanson, M.A. (2001). Performance assessment for a population of jobs. In J.P Campbell & D.J. Knapp (Eds.) *Exploring the Limits in Personnel Selection* (pp. 181-235). Mahwah, NJ: Lawrence Erlbaum.

Kuncel, N.R., Hezlett, S.A., & Ones, D.S. (2004). Academic performance, career potential, creativity and job performance: Can one construct predict them all? *Journal of Personality and Social Psychology, 86*, 148-161.

Landy, F.J. & Shankster, L.J. (1994). Personnel selection and placement. *Annual Review of Psychology, 45*, 261-296.

Levine, E.L., Spector, P.E., Menon, S., Narayanan, L., & Cannon-Bowers, J. (1996). Validity generalization for cognitive, psychomotor, and perceptual tests for craft jobs in the utility industry. *Human Performance, 9*, 1-22.

Lubinski, D. (2004) Introduction to the special section on cognitive abilities: 100 years after Spearman's (1904) "'General intelligence,' objectively determined and measured*."* *Journal of Personality and Social Psychology*, 86, 96-111.

Maraun, M.D. (1996). Metaphor taken as math: Indeterminacy in the factor analysis model. *Multivariate Behavioral Research, 31*, 517-538.

Messick, S. (1995). Validity of psychological assessment: Validation of inferences from persons' responses and performance as scientific inquiry into score meaning. *American Psychologist, 50*, 741-749.

McClelland, D.C. (1993). Intelligence is not the best predictor of job performance. *Current Directions in Psychological Science, 2*, 5-6.

McHenry, J.J., Hough, L.M., Toquam, J.L., Hanson, M.A. & Ashworth, S. (1990). Project A validity results: The relationship between predictor and criterion domains. *Personnel Psychology, 43*, 335-354.

Michell, J. (1999). *Measurement in psychology: Critical history of a methodological concept*. Camridge, UK: Cambridge University Press.

Motowidlo, S.J. & Van Scotter, J.R. (1994). Evidence that task performance should be distinguished from contextual performance. *Journal of Applied Psychology, 79*, 475-480.

Murphy, K.R. (1996). Individual differences in behavior in organizations: Much more than *g*. In K.R. Murphy (Ed.), *Individual differences and behavior in organizations* (pp.3-30). San Francisco: Jossey-Bass.

Murphy, K.R. (2002). Can conflicting perspective on the role of *g* in personnel selection be resolved? *Human Performance, 15(1/2)*, 173-186.

Murphy, K.R., Cronin, B.E, & Tam, A.P. (2003). Controversy and consensus regarding the use of cognitive ability testing in organizations. *Journal of Applied Psychology, 88*, 660-671.

Murphy, K.R. & Reynolds, D.H. (1988). Does true halo affect observed halo? *Journal of Applied Psychology, 73*, 235-238.

Mulaik, S.A. (1994). The critique of pure statistics: Artifact and objectivity in multivariate statistics. In B. Thompson (Ed.), *Advances in Social Science Methodology, Volume 3* (pp. 247-296). Greenwich: JAI Press.

Mulaik, S.A. & Quartetti, D.A. (1997). First order or higher order general factor? *Structural Equation Modeling, 4*, 193-211.

Neisser, U., Boodoo, G., Bouchard, T.J., Boykin, A.W., Brody, N., Ceci, S.J., Halpern, D.F., Loehlin, J.C., Perloff, R., Sternberg, R.J., & Urbina, S. (1996). Intelligence: Knowns and Unknowns. *American Psychologist, 51*, 77-101.

Nunnally, J.C. (1978). *Psychometric Theory.* McGraw Hill, New York.

Olea, M.M. & Ree, M.J., (1994). Predicting Pilot and Navigator Criteria: Not much more than g. *Journal of Applied Psychology, 79*, 845-851.

Ones, D.S. & Viswesvaran, C. (1996). Bandwidth-fidelity dilemma in personality for personnel selection. *Journal of Organizational Behavior, 17*, 609-626.

Oppler, S.H., McCloy, R.A, Peterson, N.G., Russell, T.L, & Campbell, J.P. (2001). The prediction of multiple components of entry-level performance. In J.P Campbell & D.J. Knapp (Eds.) *Exploring the Limits in Personnel Selection* (pp. 349-388). Mahwah, NJ: Lawrence Erlbaum.

Outtz, J.L. (2002). The role of cognitive ability tests in employment selection. *Human Performance, 15 (1/2)*, 161-171.

Paunonen, S.V. (1998). Hierarchical organization of personality and the prediction of behavior. *Journal of Personality and Social Psychology, 74*, 538-556.

Paunonen, S.V. & Ashton, M.C. (2001). Big Five factors and facets and the prediction of behavior. *Journal of Personality and Social Psychology, 81*, 524-539.

Paunonen, S.V., Rothstein, M.G., & Jackson, D.N. (1999). Narrow reasoning about the use of broad personality measures for personnel selection. *Journal of Organizational Behavior, 20,* 389-405.

Peterson, N.G., Hough, L.M., Dunnette, M.D., Rosse, R.L., Houston, J.S., Toquam, J.L., & Wing, H. (1990). Project A: Specification of the predictor domain and development of new selection/classification tests. *Personnel Psychology, 43*, 247-276.

Peterson, N.G., Mumford, M.D., Borman, W.C., Jeanneret, P.R., & Fleishman, E.A. (1999). *An occupational information system for the 21st century: The development of the O*net*. Washington, DC. American Psychological Association.

Prediger, D.J. (1989). Ability differences across occupations: More than g. *Journal of Vocational Behavior, 34*, 1-27.

Ree, M.J. & Carretta, T.R. (2002). g2k. *Human Performance, 15*(1/2), 3-23.

Ree, M.J. & Earles, J.A. (1991a). Predicting training success: Not much more than g. *Personnel Psychology, 44*, 321-332.

Ree, M.J. & Earles, J.A. (1991b). The stability of convergent estimates of g. *Intelligence, 15*, 271-278.

Ree, M.J., Earles, J.A. & Teachout, M.S. (1994). Predicting job performance: Not much more than *g*. *Journal of Applied Psychology, 79*, 518-524.

Roberts, R.D., Goff, G.N., Anjoul, F., Kyollen, P.C., Pallier, G, & Stankov, L. (2001). The Armed Services Vocational Aptitude Battery (ASVAB): Little more than acculturated learning (Gc)!? *Learning and Individual Differences, 12*, 81-103.

Rothstein, H.R. (1990). Interrater reliability of job performance ratings: Growth to asymptote level with increasing opportunity to observe. *Journal of Applied Psychology, 75*, 322-327.

Rotundo, M. & Sackett, P.R. (1999). Effect of rater race on conclusions regarding differential prediction in cognitive ability tests. *Journal of Applied Psychology, 84*, 815-822.

Russell, T.L., Peterson, N.G., Rosse, R.L., Toquam-Hatten, J., McHenry, J.J., & Houston, J.S. (2001). The measurement of cognitive, perceptual, and psychomotor abilities. In J.P Campbell & D.J. Knapp (Eds.) *Exploring the Limits in Personnel Selection* (pp. 71-109). Mahwah, NJ: Lawrence Erlbaum.

Sackett, P.R., Schmitt, N., Ellingson, J.E., & Kabin, M.B. (2001). High stakes testing in employment, credentialing and higher education: Prospects in a post affirmative action world. *American Psychologist, 56*, 302-318.

Salgado, J.F., Anderson, N., Moscoso, S., Bertua, C., Fruyt, F., & Rolland, J.P. (2003). A meta-analytic study of general mental ability validity for different occupations in the European Community. *Journal of Applied Psychology, 88*, 1068-1081.

Salgado, J.F., Anderson, N., Moscoso, S., Bertua, C., & Fruyt, F. (2003). International validity generalization of GMA and cognitive abilities: A European community meta-analysis. *Personnel Psychology, 56*, 573-605.

Schmidt, F.L. (2002). The role of general cognitive ability and job performance: Why there cannot be a debate. *Human Performance, 15*, 187-210.

Schmidt, F.L., Gast-Rosenberg, I., & Hunter, J.E. (1980). Validity generalization results for computer programmers. *Journal of Applied Psychology, 65*, 643-661.

Schmidt, F.L. & Hunter, J.E. (1977). Development of a general solution to the problem of validity generalization. *Journal of Applied Psychology, 62*, 520-540.)

Schmidt, F.L. & Hunter, J.E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin, 124*, 262-274.

Schmidt, F.L. & Hunter, J.E. (2004). General mental ability in the world of work: Occupational attainment and job performance. *Journal of Personality and Social Psychology, 86*, 162-173.

Schmidt, F.L., Onez, D.S., & Hunter, J.E. (1992). Personnel selection. *Annual Review of Psychology, 43*, 627-670.

Schneider, R.J., Hough, L.M., & Dunnette, M.D. (1996). Broadsided by broad traits: How to sink science in five dimensions or less. *Journal of Organizational Behavior, 17*, 639-655.

Schonemann, P.H. (1990). Facts, fictions, and common sense about factors and components. *Multivariate Behavioral Research, 25*, 47-51.

Schonemann, P.H. (1990). Extension of Guttman's results from g to PC1. *Multivariate Behavioral Research, 27*, 219-224.

Schonemann, P.H. (1997). Famous □rtifacts: Spearman's hypothesis. *Current Psychology of Cognition, 16*, 665-694.

Spearman, C. (1904). General intelligence objectively determined and measured. *American Journal of Psychology, 15*, 201-293.

Stankov, L. (2000). G: a diminutive general. In R.J. Sternberg & E.L. Grigorenko (Eds), *The General Factor of Intelligence: How general is it?* (pp. 19-37). Mahwah, NJ: Lawrence Earlbaum.

Sternberg, R.J. & Wagner, R.K. (1993). The g-ocentric view of intelligence and job performance is wrong. *Current Directions in Psychological Science, 2*, 1-4.

Tenopyr, M.L. (2002). Theory versus reality: Evaluation of g in the workplace. *Human Performance, 15(1/2)*, 107-122.

The Psychological Corporation. (1992). WAIS-III—WMS-III technical manual. San Antonio, TX: Author.

Tulsky, D.S. & Ledbetter, M.F. (2000). Updating to the WAIS-III and WMS-III: Considerations for research and clinical practice. *Psychological Assessment, 12*, 253-262.

Uniform Guidelines on Employee Selection Procedures (1978). Section 60-3, Uniform Guidelines on Employee Selection Procedure (1978); 43 FR 38295(August 25, 1978).

US MEPCOM (2002). *ASVAB: Educator and Counselor Guide*. Chicago: US MEPCOM.

Vinchur, A.J., Schippmann, J.S., Switzer, F.S. & Roth, P.L. (1998). A meta-analytic review of the predictors of job performance for salespeople. *Journal of Applied Psychology, 83*, 586-597.

Viswesvaran, C., & Ones, D.S. (2000). Perspectives on models of job performance. *International Journal of Selection and Assessment, 8*, 21-226.

Viswesvaran, C. & Ones, D.S. (2004). Agreements and disagreements on the role of general mental ability (GMA) in Industrial, Work and Organizational Psychology. *Human Performance, 15 (1/2)*, 211-231.

Viswesvaran, C., Ones, D.S., & Schmidt, F.L. (1996). Comparative analysis of the reliability of job performance ratings. *Journal of Applied Psychology, 81*, 557-574.

Wherry, R.J. (1931). A new formula for the predicting the shrinkage of the coefficient of multiple correlation. *Annals of Mathematical Statistics, 2*, 440-457.

Wonderlic, E.F. (1992). *Wonderlic Personnel Test user's manual*. Libertyville, IL: Wonderlic.

Table 1

Sample size and job title of the nine jobs included in the present study.

	Job (Army MOS code)	N
1	Infantryman (11B)	491
2	Cannon Crewmember (13B)	464
3	Tank Crewman (19E)	394
4	Single Channel Radio Operator (31C)	289
5	Light Wheel Vehicle Mechanic (63B)	478
6	Motor Transport Operator (64C)	507
7	Administrative Specialist (71L)	427
8	Medical Specialist (91A)	392
9	Military Police (95B)	597
Total	--	4039

Table 2

Reliability estimates and construct mapping of cognitive measures.

	Test/Scale	Ability Construct	Reliability
1	Psychometric G	General cognitive ability	--
2	AFQT	"	--
3	Arithmetic Reasoning	Mathematical Reasoning	.91
4	Math Knowledge	"	.87
5	Coding Speed	Perceptual Speed	--
6	Number Operations	Number Facility	--
7	Auto Shop	Knowledge	.87
8	Electronics Information	"	.81
9	Mechanical Comprehension	"	.85
10	General Science	"	.86
11	Paragraph Comprehension	Written Comprehension	.81
12	Word Knowledge	"	.92
13	Assembling Objects	Visualization	.91
14	Mazes	"	.96
15	Object Rotation	"	.99
16	Figural Reasoning	Inductive Reasoning	.87
17	Map	Spatial Orientation	.90
18	Orientation	"	.89
19	Cannon Shoot Test	Rate Control	.65
20	Target Shoot Test (Time to fire)	"	.85
21	Target Shoot Test (Log distance)	"	.74
22	Target Tracking 1	Control Precision	.98
23	Target Tracking 2	Multi-limb Coordination	.98
24	Short Term Memory (time)	Memorization	.96
25	Short Term Memory (% correct)	"	.60
26	Perceptual Speed & Accuracy (time)	Perceptual Speed	.94
27	Perceptual Speed & Accuracy (% correct)	"	.65
28	Target Identification (time)	"	.97
29	Target Identification (% correct)	"	.62

30	Number Memory Test (% correct)	Memorization/number facility	.59
31	Choice Reaction Time (% correct)	Response Orientation	.57
32	Choice Reaction Time (time)	“	.97
33	Simple Reaction Time (% correct)	Reaction time	.46
34	Simple Reaction Time (time)	“	.88

Table 3

Correlation matrix of predictor variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1.00																	
2	.78	1.00																
3	.69	.82	1.00															
4	.66	.82	.72	1.00														
5	.19	.20	.18	.22	1.00													
6	.14	.19	.22	.29	.53	1.00												
7	.55	.35	.32	.19	-.09	-.15	1.00											
8	.58	.45	.35	.32	-.03	-.09	.59	1.00										
9	.75	.54	.49	.45	-.01	-.07	.57	.59	1.00									
10	.69	.70	.49	.49	.04	.00	.47	.53	.54	1.00								
11	.55	.76	.44	.41	.16	.06	.28	.34	.36	.56	1.00							
12	.59	.78	.44	.45	.07	.00	.32	.43	.42	.70	.63	1.00						
13	.62	.39	.39	.38	.13	.05	.25	.25	.43	.31	.22	.23	1.00					
14	.58	.27	.28	.25	.18	.11	.23	.21	.37	.24	.16	.15	.45	1.00				
15	.52	.24	.27	.22	.12	.08	.24	.21	.36	.22	.14	.14	.36	.48	1.00			
16	.67	.51	.50	.48	.15	.12	.22	.26	.44	.38	.32	.33	.54	.39	.35	1.00		
17	.73	.56	.52	.51	.14	.10	.34	.36	.53	.46	.34	.39	.48	.40	.37	.51	1.00	
18	.62	.43	.40	.39	.08	.02	.29	.29	.46	.36	.28	.29	.43	.38	.34	.45	.51	1.00
19	-.44	-.18	-.19	-.16	-.01	-.02	-.23	-.19	-.30	-.18	-.10	-.12	-.23	-.29	-.25	-.24	-.26	-.21
20	-.34	-.13	-.13	-.10	-.05	-.06	-.18	-.13	-.22	-.16	-.09	-.10	-.14	-.25	-.21	-.18	-.18	-.17
21	-.32	-.10	-.10	-.10	-.03	.00	-.13	-.14	-.17	-.11	-.07	-.06	-.16	-.22	-.15	-.13	-.15	-.15
22	-.57	-.22	-.22	-.19	-.03	-.02	-.28	-.26	-.38	-.24	-.16	-.15	-.29	-.37	-.28	-.28	-.31	-.30
23	-.58	-.23	-.22	-.20	-.06	-.02	-.29	-.27	-.39	-.26	-.16	-.17	-.30	-.38	-.30	-.28	-.33	-.30
24	-.16	-.04	-.05	-.07	-.10	-.10	-.01	-.03	-.04	-.04	.00	.00	-.11	-.14	-.13	-.10	-.08	-.07
25	.29	.21	.18	.17	.11	.08	.06	.08	.14	.13	.16	.17	.21	.15	.10	.24	.21	.16
26	-.14	-.06	-.04	-.05	-.14	-.14	.00	-.03	-.03	-.07	-.04	-.05	-.06	-.17	-.14	-.06	-.06	-.05
27	.16	.15	.13	.13	.11	.07	.02	.04	.05	.06	.11	.09	.16	.07	.03	.15	.14	.09
28	-.48	-.23	-.19	-.20	-.08	-.06	-.23	-.22	-.31	-.29	-.17	-.18	-.30	-.41	-.35	-.27	-.28	-.25
29	.18	.14	.11	.10	.06	.00	.06	.08	.09	.11	.11	.11	.19	.08	.05	.17	.14	.09
30	-.34	-.36	-.41	-.36	-.15	-.28	-.10	-.10	-.14	-.17	-.18	-.19	-.18	-.10	-.10	-.26	-.27	-.15
31	.19	.13	.10	.08	.05	.01	.11	.11	.12	.12	.12	.12	.12	.08	.05	.14	.12	.08
32	-.20	-.09	-.08	-.09	-.13	-.14	.02	-.03	-.04	-.07	-.06	-.05	-.07	-.11	-.11	-.11	-.09	-.07
33	.15	.12	.09	.07	.04	.01	.08	.09	.09	.10	.11	.10	.07	.05	.07	.10	.08	.07
34	-.17	-.08	-.07	-.06	-.05	-.06	-.04	-.06	-.05	-.08	-.06	-.05	-.05	-.09	-.08	-.07	-.07	-.06

19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1.00															
.20	1.00														
.28	-.02	1.00													
.43	.37	.50	1.00												
.44	.36	.45	.77	1.00											
.05	.15	.04	.10	.10	1.00										
-.15	-.03	-.09	-.13	-.12	-.01	1.00									
.06	.18	-.01	.07	.09	.40	.06	1.00								
-.06	.07	-.10	-.09	-.07	.18	.27	.53	1.00							
.24	.33	.12	.32	.34	.36	-.03	.53	.24	1.00						
-.10	.10	-.17	-.11	-.08	.17	.20	.32	.37	.27	1.00					
.15	.00	.10	.11	.12	-.03	-.21	-.11	-.26	-.04	-.19	1.00				
-.01	-.02	-.05	-.08	-.06	.01	.14	.06	.15	.00	.12	-.09	1.00			
.10	.14	.10	.15	.15	.38	-.05	.26	.04	.24	.08	.05	-.02	1.00		
-.03	-.02	-.01	-.07	-.06	-.02	.05	.00	.04	-.05	.05	-.05	.17	-.06	1.00	
.10	.11	.07	.13	.12	.15	-.04	.10	-.01	.15	.01	.05	.02	.41	-.12	1.00

Table 4

Correlation matrix of criterion variables and general cognitive ability across all jobs.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Psychometric g	1.0													
2	AFQT	.78	1.0												
3	Job Knowledge (JK)	.55	.44	1.0											
4	Work Sample Performance (WS)	.32	.18	.43	1.0										
5	“Core technical prof.” WS + JK	.50	.38	.81	.67	1.0									
6	Overall performance composite	.14	.09	.24	.21	.30	1.0								
7	Technical skill rating	.19	.14	.22	.16	.29	.82	1.0							
8	Effort rating	.12	.10	.19	.14	.26	.80	.70	1.0						
9	Integrity rating	.11	.12	.14	.06	.18	.72	.58	.69	1.0					
10	Leadership rating	.13	.10	.18	.14	.26	.82	.72	.70	.61	1.0				
11	Army wide overall rating	.12	.09	.18	.13	.25	.93	.75	.75	.69	.76	1.0			
12	NCO potential rating	.09	.07	.17	.15	.24	.86	.70	.69	.63	.78	.83	1.0		
13	Promotion rate	.05	.05	.11	.10	.13	.33	.20	.20	.21	.24	.26	.25	1.0	
14	Job specific overall rating	.13	.08	.20	.17	.28	.88	.72	.64	.55	.66	.72	.68	.18	1.0

Table 5

Average rating and rater agreement of specific ability importance to job performance.

Infantry (k = 8)			Cannon Crewmember (k = 12)		
11 Raters			10 Raters		
Ability	Avg. Rating	R_{wg}	Ability	Avg. Rating	R_{wg}
reaction time	*4.82*	*0.92*	*multi-limb coordination*	*4.40*	*0.87*
multi-limb coordination	*4.45*	*0.66*	*control precision*	*4.40*	*0.64*
response orientation	*4.36*	*0.77*	*reaction time*	*4.30*	*0.77*
spatial orientation	*4.18*	*0.62*	*spatial orientation*	*4.30*	*0.55*
rate control	4.09	0.45	*response orientation*	*4.20*	*0.80*
control precision	*4.00*	*0.50*	*mechanical comprehension*	*4.10*	*0.62*
visualization	3.45	0.16	*rate control*	*4.00*	*0.67*
perceptual speed	3.27	-0.01	visualization	3.50	-0.25
memorization	3.09	0.15	perceptual speed	3.00	0.11
written comprehension	2.64	0.27	auto-shop	2.90	0.28
inductive reasoning	2.64	-0.13	memorization	2.60	-0.02
mechanical comprehension	2.45	0.06	Electrical information	2.50	0.42
auto-shop	2.27	0.19	number facility	2.40	-0.13
electrical information	2.00	0.30	written comprehension	2.10	0.28
mathematical reasoning	1.82	0.22	Inductive reasoning	2.00	0.44
number facility	1.73	0.29	mathematical reasoning	2.00	0.11
general science	1.64	0.57	general science	1.40	0.76

Tank Crewman (k = 14)			Radio Operator (k = 2)		
12 Raters			11 Raters		
spatial orientation	*4.75*	*0.90*	*electrical information*	*4.64*	*0.87*
multi-limb coordination	*4.75*	*0.90*	*mechanical comprehension*	*4.09*	*0.55*
rate control	*4.67*	*0.88*	written comprehension	3.09	0.25
control precision	*4.58*	*0.78*	memorization	2.91	0.05
reaction time	*4.58*	*0.78*	multi-limb coordination	2.64	-0.03
response orientation	*4.50*	*0.86*	Inductive reasoning	2.45	0.26
visualization	*4.17*	*0.74*	auto-shop	2.45	0.06
perceptual speed	3.83	0.29	perceptual speed	2.45	-0.04
mechanical comprehension	3.17	0.29	control precision	2.45	-0.04
memorization	3.00	0.18	reaction time	2.36	0.27
auto-shop	3.00	-0.09	Response orientation	2.36	0.17
written comprehension	2.75	0.08	visualization	2.09	0.25
inductive reasoning	2.50	0.05	rate control	2.00	0.50
electrical information	2.42	0.23	mathematical reasoning	1.91	0.45
number facility	2.17	0.20	number facility	1.82	0.62
general science	1.92	0.41	spatial orientation	1.82	0.52
mathematical reasoning	1.92	0.23	general science	1.82	0.52

Light Wheel Vehicle Mechanic (k = 3)			Motor Transport Operator (k = 5)		
10 Raters			10 Raters		
Ability	Avg. Rating	R_{wg}	Ability	Avg. Rating	R_{wg}
auto-shop	*5.00*	*1.00*	*auto-shop*	*4.56*	*0.74*
mechanical comprehension	*4.70*	*0.88*	*spatial orientation*	*4.33*	*0.88*
electrical information	*4.50*	*0.86*	*multi-limb coordination*	*4.22*	*0.53*
multi-limb coordination	3.80	0.80	*mechanical comprehension*	*4.00*	*0.63*
inductive reasoning	3.30	-0.45	rate control	3.67	0.38
visualization	2.80	0.36	reaction time	3.67	0.13
memorization	2.70	0.33	control precision	3.44	-0.01
written comprehension	2.30	0.22	visualization	3.33	-0.13
general science	2.20	0.47	response orientation	3.11	-0.06
control precision	2.20	0.24	number facility	3.00	0.50
number facility	2.00	0.56	written comprehension	2.78	0.28
rate control	1.90	0.28	memorization	2.67	0.13
response orientation	1.80	0.36	perceptual speed	2.44	0.24
mathematical reasoning	1.70	0.66	mathematical reasoning	2.33	0.38
reaction time	1.70	0.55	inductive reasoning	2.33	0.38
perceptual speed	1.60	0.76	electrical information	2.22	0.40
spatial orientation	1.60	0.42	general science	1.33	0.75

Administrative Specialist (k= 2)			Medical Specialist (k = 6)		
12 Raters			10 Raters		
written comprehension	*4.23*	*0.65*	*general science*	*4.3*	*0.55*
memorization	2.69	0.30	*memorization*	*4.1*	*0.62*
perceptual speed	2.46	0.53	*written comprehension*	*4.0*	*0.56*
number facility	2.46	0.37	multi-limb coordination	3.6	0.42
inductive reasoning	2.08	0.29	inductive reasoning	3.3	-0.34
mathematical reasoning	1.92	0.46	number facility	3.2	0.36
multi-limb coordination	1.85	0.60	reaction time	3.1	0.06
visualization	1.62	0.62	spatial orientation	2.9	0.28
control precision	1.46	0.78	response orientation	2.9	0.06
spatial orientation	1.38	0.87	visualization	2.6	0.09
reaction time	1.38	0.87	perceptual speed	2.5	0.08
response orientation	1.31	0.80	mathematical reasoning	2.4	0.20
mechanical comprehension	1.15	0.93	rate control	2.2	0.36
electrical information	1.15	0.93	control precision	2.2	0.24
rate control	1.0	1.00	electrical information	1.7	0.55
general science	1.0	1.00	mechanical comprehension	1.7	0.44
auto-shop	1.0	1.00	auto-shop	1.4	0.76

Military Police (k = 4)		
10 Raters		
Ability	Avg. Rating	R_{wg}
spatial orientation	*4.1*	*0.95*
reaction time	4.0	0.22
response orientation	*3.8*	*0.69*
multi-limb coordination	3.7	0.55
written comprehension	3.4	0.64
inductive reasoning	3.3	0.11
perceptual speed	3.3	-0.34
memorization	3.2	0.24
rate control	2.9	0.28
visualization	2.8	0.02
control precision	2.7	0.44
number facility	2.1	0.39
mechanical comprehension	2.0	0.33
mathematical reasoning	1.8	0.58
general science	1.7	0.77
auto-shop	1.7	0.66
electrical information	1.3	0.88

Specific ability constructs deemed job related are in italics. k = the number of predictor variables that comprise the job related specific ability composite.

Table 6

Correlation and multiple correlation coefficients of predictor and criterion variables by job.

Criterion	rg_1	rg_2	rg_3	R_{jrs}	R_{jrs+g3}	Δ_1R^2	Δ_2R^2
			Infantry				
Work Sample	.349	.257	.332	.317	.351	.022**	.013
Job Knowledge	.629	.503	.616	.615	.663	.062**	.061**
WS+JK	.581	.456	.564	.543	.594	.058**	.035**
Overall perf.	.280	.193	.264	.331	.336	.003ns	.043**
			Cannon Crewmember				
Work Sample	.234	.138	.211	.284	.289	.003ns	.039ns
Job Knowledge	.505	.378	.499	.496	.545	.051**	.047**
WS+JK	.428	.306	.411	.437	.464	.025**	.047**
Overall perf.	.122	.063	.105	.213	.213	.000ns	.034**
			Tank Crewmember				
Work Sample	.372	.267	.333	.440	.443	.003ns	.086**
Job Knowledge	.664	.540	.646	.660	.707	.065**	.084**
WS+JK	.604	.468	.571	.628	.650	.029**	.097**
Overall perf.	.219	.169	.221	.285	.296	.006ns	.039ns
			Radio Operator				
Work Sample	.336	.329	.315	.301	.336	.022**	.014ns
Job Knowledge	.501	.427	.484	.374	.491	.101**	.007ns
WS+JK	.455	.415	.433	.372	.447	.061**	.012ns
Overall perf.	.173	.085	.153	.193	.196	.001ns	.015ns
			Light Wheel Vehicle Mechanic				
Work Sample	.278	.126	.252	.280	.308	.017**	.031**
Job Knowledge	.557	.438	.523	.530	.584	.060**	.068**
WS+JK	.509	.341	.473	.481	.536	.056**	.063**
Overall perf.	.082ns	.020ns	.050ns	.176	.192	.006ns	.034**
			Motor Transport Operator				
Work Sample	.402	.239	.390	.416	.439	.020**	.040**
Job Knowledge	.586	.476	.567	.528	.587	.066**	.024**
WS+JK	.580	.426	.561	.546	.594	.055**	.038**
Overall perf.	.094	.014ns	.103	.187	.193	.002ns	.027**
			Administrative Specialist				
Work Sample	.395	.335	.398	.219	.412	.121**	.011ns
Job Knowledge	.592	.542	.582	.422	.597	.178**	.018**
WS+JK	.556	.496	.553	.354	.561	.189**	.009ns
Overall perf.	.169	.202	.159	.147	.181	.011*	.007ns
			Medical Specialist				
Work Sample	.393	.285	.381	.320	.415	.069**	.027ns
Job Knowledge	.463	.374	.432	.424	.502	.072**	.065**
WS+JK	.504	.383	.479	.429	.532	.099**	.054**
Overall perf.	.10	.076ns	.098	.098ns	.136ns	.009ns	.009ns
			Military Police				

Work Sample	.401	.246	.381	.320	.403	.060**	.018*
Job Knowledge	.478	.339	.449	.377	.469	.078**	.080**
WS+JK	.528	.351	.501	.414	.525	.104**	.024**
Overall perf.	.148	.089	.145	.141	.172	.010*	.009ns

*rg_1 is the correlation for psychometric g estimated from all variables, $rg_2$is the correlation for the AFQT, rg_3 is the correlation for psychometric g estimated from cognitive measures not included in "job related specific abilities," R_{jrs} is the multiple correlation for job related specific ability composites. All correlations and multiple correlations are significant at the .01 level unless indicated otherwise. $\Delta_1 R^2$ is what g_3 adds to a model containing jrs, $\Delta_2 R^2$ is what jrs adds to a model containing g_3. *p<.05 **p<.01.*

Table 7

Squared validity coefficients corrected for cross validation.

Criterion	ρ^2_{g1}	ρ^2_{g2}	ρ^2_{g3}	ρ^2_{jrs}	ρ^2_{jrs+g3}
Infantry					
Work Sample	.120	.064	.108	.086	.107
Job Knowledge	.394	.251	.378	.368	.429
WS+JK	.336	.206	.317	.283	.341
Overall perf.	.077	.035	.068	.095	.096
Cannon Crewmember					
Work Sample	.053	.017	.042	.056	.057
Job Knowledge	.253	.141	.247	.226	.277
WS+JK	.181	.092	.167	.169	.193
Overall perf.	.013	.002	.009	.020	.018
Tank Crewmember					
Work Sample	.136	.069	.109	.164	.164
Job Knowledge	.439	.290	.416	.415	.480
WS+JK	.363	.217	.324	.372	.400
Overall perf.	.046	.026	.046	.047	.051
Radio Operator					
Work Sample	.110	.105	.096	.084	.104
Job Knowledge	.248	.179	.232	.134	.233
WS+JK	.204	.169	.185	.132	.191
Overall perf.	.027	.004	.020	.031	.028
Light Wheel Vehicle Mechanic					
Work Sample	.075	.014	.062	.073	.087
Job Knowledge	.309	.190	.272	.276	.335
WS+JK	.258	.114	.222	.226	.281
Overall perf.	.005	-.002	.000	.025	.029
Motor Transport Operator					
Work Sample	.160	.055	.150	.165	.183
Job Knowledge	.342	.225	.320	.272	.337
WS+JK	.335	.180	.313	.291	.345
Overall perf.	.007	-.002	.009	.025	.026
Administrative Specialist					
Work Sample	.154	.110	.156	.043	.164
Job Knowledge	.349	.292	.337	.174	.352
WS+JK	.308	.244	.304	.121	.310
Overall perf.	.026	.039	.023	.017	.026
Medical Specialist					
Work Sample	.152	.079	.143	.088	.157
Job Knowledge	.212	.138	.185	.167	.238
WS+JK	.252	.145	.227	.171	.270
Overall perf.	.007	.003	.007	-.006	.001
Military Police					

Work Sample	.159	.059	.144	.096	.155
Job Knowledge	.227	.113	.200	.136	.213
WS+JK	.278	.122	.250	.166	.269
Overall perf.	.020	.006	.019	.013	.021

ρ^2_{g1} *is the estimated population squared cross validity coefficient for psychometric g estimated from all variables,* ρ^2_{g2} *is the estimated population squared cross validity coefficient for the AFQT,* ρ^2_{g3} *is the estimated population squared cross validity coefficient for psychometric g estimated from cognitive measures not included in "job related specific abilities,"* ρ^2_{jrs} *is the estimated population squared cross validity coefficient for job related specific ability composites.*

Table 8

Predicted residual sum of squares (PRESS) for general cognitive ability and job related specific ability composites.

Criterion	$PRESS_{g1}$	$PRESS_{g2}$	$PRESS_{g3}$	$PRESS_{jrs}$
Infantry				
Work Sample	27205	28950	27565	28732
Overall perf.	3523	3694	3561	3515
Cannon Crewmember				
Work Sample	49417	51117	49942	50646
Overall perf.	3196	3226	3209	3236
Tank Crewmember				
Work Sample	17677	19105	18282	17943
Overall perf.	2695	2750	2695	2793
Radio Operator				
Work Sample	19554	19654	19864	20188
Overall perf.	2020	2065	2035	2014
Light Wheel Vehicle Mechanic				
Work Sample	12501	13365	12692	12619
Overall perf.	3265	3296	3282	3207
Motor Transport Operator				
Work Sample	26399	29638	26695	26543
Overall perf.	3582	3628	3573	3571
Administrative Specialist				
Work Sample	35531	37457	35420	40556
Overall perf.	3073	3041	3084	3116
Medical Specialist				
Work Sample	19819	21569	20039	21557
Overall perf.	2862	2875	2863	2938
Military Police				
Work Sample	22152	24779	22567	23923
Overall perf.	4545	4608	4546	4607

$PRESS_{g1}$ *is the predicted residual sum of squares for psychometric g estimated from all variables* $PRESS_{g2}$ *is the predicted residual sum of squares for the AFQT, the predicted residual sum of squares for psychometric g estimated from cognitive measures not included in "job related specific abilities,"* $PRESS_{jrs}$ *is the predicted residual sum of squares for job related specific ability composites.*

Table 9

Convergent and discriminant validity of job related specific ability composites.

	Job Related Specific Ability Composite Predicting Work Sample Performance								
	Infantry	Cannon	Tank	Radio	Mechanic	Motor	Admin	Medical	Police
Infantry	***.32***	.33	.33	.26	.29	.35	.20	.34	.30
Cannon	.27	***.28***	.28	.20	.21	.25	.11	.19	.22
Tank	.40	.42	***.44***	.33	.33	.39	.18	.29	.37
Radio	.26	.33	.29	***.30***	.31	.32	.25	.30	.25
Mechanic	.26	.30	.32	.24	***.28***	.31	.11	.20	.20
Motor	.37	.42	.42	.35	.39	***.42***	.15	.28	.33
Admin	.38	.39	.43	.21	.22	.37	***.22***	.36	.38
Medical	.32	.37	.37	.29	.30	.35	.17	***.32***	.31
Police	.34	.39	.37	.32	.33	.38	.10	.27	***.32***
	Job Related Specific Ability Composite Predicting Overall Performance								
	Infantry	Cannon	Tank	Radio	Mechanic	Motor	Admin	Medical	Police
Infantry	***.33***	.35	.35	.18	.19	.33	.14	.24	.31
Cannon	.17	***.21***	.21	.08	.08	.14	.05	.12	.14
Tank	.25	.34	***.29***	.23	.23	.27	.20	.24	.31
Radio	.20	.29	.27	***.19***	.22	.25	.00	.19	.16
Mechanic	.16	.26	.22	.20	***.18***	.24	.01	.09	.08
Motor	.14	.22	.22	.15	.17	***.19***	.05	.12	.09
Admin	.16	.21	.21	.11	.15	.16	***.15***	.20	.15
Medical	.12	.16	.19	.10	.13	.16	.06	***.10***	.09
Police	.17	.19	.19	.14	.16	.18	.12	.16	***.14***

Table 10

Convergent and discriminant validity of the incremental variance (ΔR^2) of job related specific ability composites.

	Job Related Specific Ability Composite Predicting Work Sample Performance								
	Infantry	Cannon	Tank	Radio	Mechanic	Motor	Admin	Medical	Police
Infantry	***.013***	.015	.024	.001	.009	.019	.008	.032	.032
Cannon	.036	***.039***	.040	.004	.006	.019	.008	.009	.009
Tank	.055	.067	***.086***	.016	.016	.045	.022	.027	.027
Radio	.017	.046	.042	***.014***	.018	.020	.007	.012	.003
Mechanic	.012	.027	.042	.013	***.031***	.036	.005	.022	.003
Motor	.023	.039	.040	.012	.036	***.040***	.007	.010	.018
Admin	.018	.046	.044	.020	.024	.040	***.011***	.036	.011
Medical	.015	.028	.032	.001	.003	.017	.004	***.027***	.002
Police	.026	.038	.033	.016	.017	.026	.001	.017	***.018***
	Job Related Specific Ability Composite Predicting Overall Performance								
	Infantry	Cannon	Tank	Radio	Mechanic	Motor	Admin	Medical	Police
Infantry	***.043***	.045	.046	.002	.002	.030	.010	.013	.013
Cannon	.019	***.035***	.037	.001	.001	.011	.008	.018	.018
Tank	.022	.042	***.039***	.003	.007	.019	.029	.032	.032
Radio	.032	.059	.052	***.015***	.019	.031	.015	.024	.026
Mechanic	.026	.074	.054	.028	***.034***	.051	.003	.007	.011
Motor	.015	.034	.034	.009	.017	***.027***	.022	.024	.011
Admin	.019	.034	.034	.001	.006	.009	***.007***	.018	.008
Medical	.006	.023	.030	.012	.018	.018	.003	***.009***	.001
Police	.018	.025	.034	.008	.017	.026	.003	.010	***.009***

Table 11

Standardized black-white differences on specific ability measures.

	Test/Scale	Ability Construct	D-score
1	Psychometric G	General cognitive ability	1.59
2	AFQT	"	.98
3	Arithmetic Reasoning	Mathematical Reasoning	0.89
4	Math Knowledge	"	0.59
5	Coding Speed	Perceptual Speed	0.20
6	Number Operations	Number Facility	-0.03
7	Auto Shop	Knowledge	1.31
8	Electronics Information	"	0.93
9	Mechanical Comprehension	"	1.19
10	General Science	"	1.21
11	Paragraph Comprehension	Written Comprehension	0.80
12	Word Knowledge	"	0.89
13	Assembling Objects	Visualization	0.86
14	Mazes	"	1.10
15	Object Rotation	"	0.78
16	Figural Reasoning	Inductive Reasoning	0.79
17	Map	Spatial Orientation	1.09
18	Orientation	"	0.85
19	Cannon Shoot Test	Rate Control	-0.66
20	Target Shoot Test (Time to fire)	"	-0.64
21	Target Shoot Test (Log distance)	"	-0.28
22	Target Tracking 1	Control Precision	-0.88
23	Target Tracking 2	Multi-limb Coordination	-0.95
24	Short Term Memory (time)	Memorization	-0.07
25	Short Term Memory (% correct)	"	0.26
26	Perceptual Speed & Accuracy (time)	Perceptual Speed	-0.02
27	Perceptual Speed & Accuracy (% correct)	"	0.18
28	Target Identification (time)	"	-0.77
29	Target Identification (% correct)	"	0.25
30	Number Memory Test (% correct)	Memorization/number facility	-0.34
31	Choice Reaction Time (% correct)	Response Orientation	0.39
32	Choice Reaction Time (time)	"	-0.13
33	Simple Reaction Time (% correct)	Reaction time	0.34
34	Simple Reaction Time (time)	"	-0.16

N White = 2930, N Black = 848

Table 12

Standardized black-white differences on predicted and actual performance.

Job(s)	Predictor/composite	N White	N Black	Predicted Work Sample Performance D-score	Actual Work Sample Performance D-Score
All	Psychometric G	2930	848	1.59	0.52
All	AFQT	2930	848	.98	“
Infantry	Job related specific abilities	403	49	1.23	0.43
Cannon	Job related specific abilities	250	168	1.33	0.27
Tank	Job related specific abilities	297	71	1.47	0.70
Radio	Job related specific abilities	204	74	0.90	0.40
Mechanic	Job related specific abilities	374	78	1.38	0.47
Motor	Job related specific abilities	358	121	1.43	0.55
Admin	Job related specific abilities	235	159	0.76	0.26
Medical	Job related specific abilities	260	91	0.92	0.48
Police	Job related specific abilities	549	37	0.53	0.33
Job(s)	Predictor/composite	N White	N Black	Predicted Overall Performance D-score	Actual Overall Performance D-Score
All	Psychometric G	2930	848	1.59	0.15
All	AFQT	2930	848	.98	“
Infantry	Job related specific abilities	403	49	1.06	0.30
Cannon	Job related specific abilities	250	168	1.01	0.19
Tank	Job related specific abilities	297	71	1.10	0.29
Radio	Job related specific abilities	204	74	0.86	0.10
Mechanic	Job related specific abilities	374	78	1.45	0.14
Motor	Job related specific abilities	358	121	0.93	-0.04
Admin	Job related specific abilities	235	159	0.77	0.24
Medical	Job related specific abilities	260	91	0.60	0.26
Police	Job related specific abilities	549	37	0.46	0.07

Appendix A

General Science

Tests the ability to answer questions on a variety of science topics drawn from courses taught in most high schools. The life science items cover botany, zoology, anatomy and physiology, and ecology. The earth and space science items are based on astronomy, geology, meteorology, and oceanography. The physical science items measure force and motion mechanics, energy, fluids, atomic structure, and chemistry.

Arithmetic Reasoning

Tests the ability to solve basic arithmetic problems encountered in everyday life. One-step and multi-step word problems require addition, subtraction, multiplication, and division, and choosing the correct order of operations when more than one step is necessary. The items include operations with whole numbers, operations with rational numbers, ratio and proportion, interest and percentage, and measurement. Arithmetic reasoning is one factor that helps characterize mathematics comprehension and it also assesses logical thinking.

Word Knowledge

Tests the ability to understand the meaning of words through synonyms – words having the same or nearly the same meaning as other words. The test is a measure of one component of reading comprehension since vocabulary is one of many factors that characterize reading comprehension.

Paragraph Comprehension

Tests the ability to obtain information from written material. Students read different types of passages of varying lengths and respond to questions based on information presented in each passage. Concepts include identifying stated and reworded facts, determining a sequence of events, drawing conclusions, identifying main ideas, determining the author's purpose and tone, and identifying style and technique.

Numerical Operations

A speeded test requiring rapid and accurate computation of simple two number problems presented as: 2+3=____. All numbers were one- or two-digit whole numbers; addition, subtraction, multiplication, and division are equally represented.

Coding Speed

A speeded test requiring rapid and accurate matching of four digit numbers with single words from a key. Coding Speed items were developed by utilizing a dictionary for selection of common usage words consisting of three to ten letters each.

Auto-Shop

Tests aptitude for automotive maintenance and repair and wood and metal shop practices. The test covers several areas commonly included in most high school auto and shop courses such as automotive components, automotive systems, automotive tools, troubleshooting and repair, shop tools, building materials, and building and construction procedures.

Mathematics Knowledge

Tests the ability to solve problems by applying knowledge of mathematical concepts and applications. The problems focus on concepts and algorithms and involve number theory, numeration, algebraic operations and equations, geometry and measurement, and probability. Mathematics knowledge is one factor that characterizes mathematics comprehension; it also assesses logical thinking.

Mechanical Comprehension

Tests understanding of the principles of mechanical devices, structural support, and properties of materials. Mechanical comprehension topics include simple machines, compound machines, mechanical motion and fluid dynamics.

Electrical Information

Tests understanding of electrical current, circuits, devices, and systems. Electronics information topics include electrical tools, symbols, devices, and materials; electrical circuits; electrical and electronic systems; and electrical currents.

Assembling Objects

The ability to mentally manipulate components of two or three-dimensional figures into other arrangements. More specifically, the ability to examine a set of components and choose among a number of alternatives which object depicts the components or parts put together correctly.

Object Rotation

The ability to mentally manipulate components of two or three-dimensional figures into other arrangements. More specifically, the ability to examine a test object and determine whether the figure represented in each item is the same as the test object, only rotated, or is not the same as the test object.

Maze

The ability to visually survey a complex field and find a pathway through it. The ability to determined which of four entrances leads to a pathway through the maze and to one of the exit points.

Orientation

The ability to maintain one's bearings and maintain location. Tests the ability to mentally rotate a frame and then determine the relative location of an object.

Maps

The ability to maintain one's bearings with respect to points on a compass and maintain location relative to landmarks. The ability to determine the relative location of landmarks on a map using compass directions and their own location on the map.

Figural Reasoning

The ability to generate hypotheses about principles governing relationships among several objects. Test the ability to determine which figure should appear next when presented with a series of four figures.

Simple Reaction Time

Tests the speed of reaction to stimuli. For example, the word "yellow" appears on a computer screen and the subject must move his hand from the "home" button and strike a yellow key.

Choice Reaction time

Tests the speed of reaction to stimuli. For example, the word "blue" or "white" appears a computer screen and the subject must move his hand from the home button and strike the key corresponding to the word appearing on the screen.

Short Term Memory

The rate at which an individual observes, searches and recalls information contained in short term memory.

Perceptual Speed and Accuracy

The ability to make a rapid comparison of two visual stimuli presented simultaneously and determine whether they are the same or different.

Target Identification

The ability to identify which of three stimuli represent the same object (military vehicle/aircraft) as the target stimuli.

Target Tracking 1

The ability to make muscular movements necessary to adjust or position a machine control mechanism. The ability to keep crosshairs centered on a moving target using a one-hand joystick.

Target Tracking 2

The ability to make muscular movements necessary to adjust or position a machine control mechanism in conjunction with the ability to coordinate two or more moving limbs. The ability to keep crosshairs centered on a moving target using two sliding resistors (one vertical and one horizontal).

Number Memory

The ability to perform, quickly and accurately, simple arithmetic operations such as addition, subtraction, multiplication and division.

Cannon Shoot Test

The ability to judge the relative speed and direction of one or more moving objects to determine where those objects will be at a given point in time and/or when those objects might intersect.

Appendix B

Directions:

Below you will find a description of a common military job. Please read over the description carefully and detach this sheet so that you may refer back to it when responding to the questions that follow. On the following pages you will be presented with descriptions of a number of psychological constructs. Your task is to rate the importance of each construct to performance in the job described on this page using the scale provided. Please mark all of your responses on the opscan form.

Administrative Specialist:

Accurate information is crucial for planning and managing Army operations. Administrative Specialists make sure that information is recorded, stored and delivered in order to keep operations running as smoothly as possible. Administrative Specialist duties include:

- Typing letters, reports, requisition forms and official orders
- Organizing and maintaining files and publications
- Ordering office supplies
- Greeting and assisting office visitors
- Scheduling training and leave for unit personnel
- Answering phones and providing general information
- Safeguarding classified documents

***Written comprehension** is the ability to understand written sentences and paragraphs. This ability involves reading and understanding the meaning of words, phrases, sentences and paragraphs. It involves reading; it does not involve writing, listening to, or understanding spoken information*

1). How important is **written comprehension** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

***Memorization** is the ability to remember information such as words, numbers, pictures and procedures. Pieces of information can be remembered by themselves or with other pieces of information. This ability emphasizes episodic memory (memory for specific events) rather than semantic memory (memory of general knowledge).*

2). How important is **memorization** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

***Mathematical reasoning** is the ability to understand and organize a problem and then to select a mathematical method or formula to solve the problem. It encompasses reasoning through mathematical problems to determine appropriate operations that can be performed to solve problems. It also includes the understanding or structuring of mathematical problems. The actual manipulation of numbers is not included in this ability.*

3). How important is **Mathematical reasoning** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

***Number facility** is the ability to add, subtract, multiply, divide, and manipulate numbers quickly and accurately. It is required for steps in other operations, such as finding percentages and taking square roots. This ability does not involve understanding or organizing mathematical problems.*

4). How important is **Number facility** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

***Inductive reasoning** is the ability to combine separate pieces of information, or specific answers to non-mathematical problems, or to form general rules or conclusions. In involves the ability to think of possible reasons why things go together, such as giving a logical explanation for a series of events that seem unrelated. It involves forming the best general rule, rather than producing many rules or applying a previously formed rule. It is sometimes seen as the forming and testing of hypotheses.*

5). How important is **Inductive reasoning** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

***Spatial orientation** is the ability to know one's location in relation to the environment one is in or to know where an object is in relation to oneself. It involves maintaining directional orientation in one's bearings with respect to the points on a compass. This ability allows one to stay oriented in a vehicle as it changes location and direction. It helps prevent disorientation while in a new environment.*

6). How important is **Spatial orientation** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Visualization *is the ability to imagine how something will look when it is moved around or when its parts are moved or rearranged. This ability requires the forming of mental images of how patterns or objects would look after certain changes, such as unfolding or rotation. One has to predict how an object, set of objects, or pattern will appear after the changes have been made.*

7). How important is **Visualization** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Perceptual speed *is the ability to compare letters, numbers, objects, pictures or patterns, quickly and accurately. The stimuli to be compared may be presented at the same time or in succession. This ability also includes comparing a presented object with a remembered object.*

8). How important is **Perceptual speed** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Control precision *is the ability to make highly controlled and precise adjustments in moving the controls of a machine or vehicle quickly and repeatedly to exact positions. It involves quick or continuous adjustments rather than the timing or rapid choice of movements.*

9). How important is **Control precision** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Multi-limb coordination *is the ability to coordinate movements of two or more limbs (e.g. two arms, two legs, or one leg and one arm), for example, while moving equipment controls. Two or more limbs are in motion while the individual is sitting, standing, or lying down. This ability does not involve performing these activities while the body is in motion.*

10). How important is **Multi-limb coordination** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Response orientation *is the ability to choose between two or more movements quickly and correctly when two or more different signals (lights, sounds, pictures) are given. The ability is concerned with the speed with which the correct response can be started with the hand, foot, or other parts of the body. This ability has sometimes been called Choice Reaction Time.*

11). How important is **Response orientation** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Rate control *is the ability to adjust an equipment control in response to changes in the speed and/or direction or a continuously moving object or scene. The ability involves timing the adjustments and anticipating changes. This ability does not extend to situations in which both the speed and the direction of the objects are perfectly predictable.*

12). How important is **Rate control** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Reaction time *is the ability to give a fast response to a signal (light, sound or picture) when it appears. This ability is concerned with the speed with which the movement can be started with the hand, foot, or other parts of the body, but is not the speed with which the movement is carried out once started. It does not involve choosing which response to make. This ability is not measured when more than one type of signal must be discriminated or more than one type of response chosen.*

13). How important is **Reaction time** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

General science *involves knowledge of a variety of science topics drawn from courses taught in most high schools. The life science items cover botany, zoology, anatomy and physiology, and ecology. The earth and space science items are based on astronomy, geology, meteorology, and oceanography. The physical science items measure force and motion mechanics, energy, fluids, atomic structure, and chemistry.*

14). How important is **General science** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Auto-Shop *involves aptitude for automotive maintenance and repair and wood and metal shop practices. The test covers several areas commonly included in most high school auto and shop courses such as automotive components, automotive systems, automotive tools, troubleshooting and repair, shop tools, building materials, and building and construction procedures.*

15). How important is **Auto-Shop** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Mechanical comprehension *involves understanding of the principles of mechanical devices, structural support, and properties of materials. Mechanical comprehension topics include simple machines, compound machines, mechanical motion and fluid dynamics.*

16). How important is **Mechanical comprehension** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

***Electrical information** involves understanding of electrical current, circuits, devices, and systems. Electronics information topics include electrical tools, symbols, devices, and materials; electrical circuits; electrical and electronic systems; and electrical currents.*

17). How important is **Electrical information** to the performance in the job of **administrative specialist**?

Not Important	Somewhat Important	Important	Very Important	Extremely Important
1	**2**	**3**	**4**	**5**

Appendix C

Infantryman

The infantry is the main land combat force and backbone of the Army. It's equally important in peacetime and in combat. The Infantryman's role is to be ready to defend our country in peacetime and to capture, destroy and repel enemy ground forces during combat.

The following are some duties expected of Infantrymen:

- Perform as a member of a fire team during drills and live combat
- Perform hand-to-hand combat
- Aid in the mobilization of vehicles, troops and weaponry
- Assist in reconnaissance missions
- Operate two-way radios and signal equipment
- Process prisoners of war and captured documents
- Learn to use, maintain and store various combat weaponry (rifles, machine guns, anti-tank mines, etc.)

Cannon Crewmember

A Cannon Crewmember is an important part of the Army's success on the battlefield. Artillery teams are used to support infantry and tank units in combat, but also have responsibilities during peacetime. Cannon Crewmembers work on cannons known as 'howitzers,' a heavy artillery machine piece with single-barrel firing capability.

Here are some of the duties of a Cannon Crewmember:

- Starts and maintains wire and radio communications
- Identifies target locations
- Sight and fire on targets with howitzer cannon
- Driving vehicles including self-propelled howitzers, ammunition trucks and other vehicles
- Disassemble/perform maintenance on components of the howitzer cannon

Tank Crewman

The Tank Crewman works as part of a team to operate armored equipment and fire weapons to destroy enemy positions. During peacetime, tank and armor units must stay ready to defend our country anywhere in the world. During combat, their role is to operate tanks and amphibious assault vehicles to engage and destroy the enemy. Tanks like the M1A2 Abrams use mobility, firepower and shock effect to close with and extinguish enemy forces.

Some the duties of a Tank Crewman may include:

- Assisting in target detection and identification
- Loading and firing guns
- Operating two-way radios and signaling equipment to receive and relay battle orders
- Operating main gun controls and firing controls
- Operating tracked and wheeled vehicles over varied terrain
- Operating internal communications equipment
- Selecting tank routes
- Positioning vehicles in firing positions

- Reading maps, compasses and battle plans

Radio Operator

As one of the largest ground forces in the world, the U.S. Army needs to make sure that all forces can get the correct information. The Army communications maintenance team is responsible for making sure that all communications equipment is in top working order. This equipment allows the Army to track and direct troop, aircraft and watercraft movements.

Radio Operator/Maintainers are primarily responsible for all maintenance checks and services on assigned radio communication equipment. Some of the duties of a Radio Operator may include:

- Maintaining, testing and repairing communications equipment and security devices
- Preparing and transmitting messages
- Receiving, recording and processing messages
- Operating and performing preventive maintenance checks on assigned equipment
- Installing, operating and performing preventive maintenance checks on assigned power generators

Light Wheel Vehicle Mechanic

The success of Army missions depends on keeping automotive and heavy equipment in top working condition. As an integral member of the Mechanical Maintenance team, the Light-Wheel Vehicle Mechanic handles the maintenance and repair of vehicles such as jeeps, cars and trucks.

The Light-Wheel Vehicle Mechanic is primarily responsible for supervising and performing maintenance and recovery operations on light-wheeled vehicles and associated items, as well as heavy-wheeled vehicles. Some of the duties of a Light-Wheel Vehicle Mechanic may include:

- Maintaining power-assisted brake systems, wheeled vehicle suspension systems, wheel/hub assemblies and wheeled vehicle hydraulic steering systems
- Troubleshooting problems in vehicle engines, electrical systems, steering, brakes and suspensions
- Tuning and repairing engines
- Replacing or repairing damaged auto-body parts
- Establishing and following schedules for maintaining vehicles

Motor Transport Operator

The United States Armed forces own and operate over 50,000 heavy trucks and buses. It's up to the Motor Transport Operators to operate vehicles, which include water/fuel tank trucks, semi-tractor trailers, heavy troop transports and passenger buses. From sedans to semi tractor trailers, troop transports and buses.

Motor Transport Operators are primarily responsible for supervising or operating wheel vehicles to transport personnel and cargo. Some of the duties of a Motor Transport Operator may include:

- Reading load plans
- Using maps and following routes
- Determine distances on a map
- Determine grid coordinates on a map

- Checking oil, fuel and other fluid levels, as well as tire pressure
- Driving vehicles over all types of roads and terrain, traveling alone or in convoys in support of combat operations
- Keeping records of mileage driven and fuel and oil used
- Washing vehicles and perform routine maintenance and repairs

Administrative Specialist:

Accurate information is crucial for planning and managing Army operations. Administrative Specialists make sure that information is recorded, stored and delivered in order to keep operations running as smoothly as possible. Administrative Specialist duties include:

- Typing letters, reports, requisition forms and official orders
- Organizing and maintaining files and publications
- Ordering office supplies
- Greeting and assisting office visitors
- Scheduling training and leave for unit personnel
- Answering phones and providing general information
- Safeguarding classified documents

Medical Specialist

The medical specialist provides health care to army personnel and is often a first responder in medical emergencies. Medical specialists provide basic emergency medical treatment to those injured or ill. Some of the duties of a medical specialist include:

- Maintaining medical supplies and keeping medical records
- Dispensing medications
- Splinting a suspected fracture, opening a blocked airway, putting on field dressing.
- Recording injury/illness and treatment during combat
- Assembling needle/administering an injection
- Initiating and IV
- Performing CPR
- Checking vital signs such as pulse, respiration, blood pressure.
- Reading a map and determining grid coordinates

Military Police

Crimes can happen anywhere and the Army is no exception. Fortunately, the Army has their own law enforcement and security specialists to handle crimes committed on Army property or that involve Army personnel. Military Police protect lives and property on Army bases by enforcing military laws and regulations, as well as controlling traffic, preventing crime and responding to emergencies.

Military Police are primarily responsible for providing support to the battlefield by conducting area security, prisoner of war and law and order operations. Some the duties of a member of the Military Police team may include:

- Patrolling areas on foot, by car or by boat
- Interviewing witnesses, victims and suspects in the course of investigating crimes
- Guarding entrances and direct traffic
- Performing basic first aid and CPR
- Responding to emergencies
- Prepare military police reports
- Reading and determining grid coordinates on a map
- Operating and maintaining firearms

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EDUCATION

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Virginia Tech, Blacksburg, VA
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B.S., Psychology, May 1999
College of Charleston, Charleston, SC

TEACHING EXPERIENCE, VIRGINIA TECH

Instructor: *Principles of Psychological Research (PSYC 2094),* **2003, 2004**.
Course designed to instruct students in the fundamentals of scientific reasoning, experimental design and data analysis. Responsible for all aspects of the course, including textbook selection, course design, lectures, activities and exams.
OVERALL RATING = 3.4 DEPARTMENTAL AVERAGE FOR PSYC 2094 = 3.4[1]

Instructor: *Laboratory in Advanced Social Psychology (PSYC 4284),* **2001.**
Course designed to give students hands on experience in conducting behavioral research and introduce them to scientific writing. Supervised the design, execution and APA style write up of social psychology field research.
OVERALL RATING = 3.6 DEPARTMENTAL AVERAGE FOR PSYC 4284 = 3.5.

Teaching Assistant: *Introductory Psychology (PSYC 2004),* **2000.**
Instructor for recitation sections, which are designed to supplement Introductory Psychology Lecture. Introduces students to broad topics in behavioral research, including social, cognitive, learning, bio-bases and I/O.

WORK EXPERIENCE

Graduate Assistant: *Virginia Tech Office of Institutional Research*, **2002-Present.**
Managed large-scale "student census" database.
Respond to various institutional requests that require the use of descriptive and inferential statistics.

Research Assistant: *Georgia Institute of Technology*, **1999-2000.**
Part time research assistant for P.L Ackerman in his I-O Lab.

Document Clerk: *Tort Litigation Team: King & Spalding (Atlanta, GA)*, **1999-2000.**
Created and maintained intricate document database for medical records and production documents in multi-million dollar litigation

[1] This departmental average includes faculty instructors. There are 6 teaching award winners among these psychology faculty instructors. The highest possible rating is 4.0.

MANUSCRIPT UNDER REVIEW

Trippe, D.M. (2004). Equivalence of online and traditional forms of a Five Factor Model measure. Manuscript under review at *Organizational Research Methods*.

CONFERENCE PRESENTATIONS[2]

Trippe, D.M. (2005). *Equivalence of online and traditional forms of a Five Factor Model measure*. Poster to be presented at the 20th Annual Conference for the Society of Industrial Organizational Psychology, Los Angeles, California. *Selected for Interactive Poster Session in Internet-Based Measurement.*

Trippe, D. M. & Foti, R.J. (2003). *An evaluation of the construct validity of Situational Judgment Tests*. Poster presented at the 18th Annual Conference for the Society of Industrial Organizational Psychology, Orlando, Florida.

Trippe, D. M. & Harvey, R.J. (2003). *IRT analysis of the International Personality Item Pool "Big Five" Scales*. Poster presented at the 18th Annual Conference for the Society of Industrial Organizational Psychology, Orlando, Florida.

Hollander, E., Trippe, D.M., Hafsteinsson, L.G., Watt, A., Quintela, Y. (2003). *Attribution Theory and Diffusion of Responsibility Applied to Electronic Correspondence*. Poster presented at the 18th Annual Conference for the Society of Industrial Organizational Psychology, Orlando, Florida

PROFESSIONAL MEMBERSHIPS

Society for Industrial Organizational Psychology
American Psychological Association
Psi Chi

AWARDS

Virginia Tech Psychology Department Galper Fund Award
Virginia Tech Graduate Research Development Project Award
Virginia Tech Graduate Student Association Travel Award

QUANTITATIVE/COMPUTER SKILLS

Item Response Theory: *Bilog, Multilog, Equate, DFIT.*
Structural Equation Modeling/Confirmatory Factor analysis: *LISREL, CALIS (SAS)*
Hierarchical Linear Modeling: *HLM*
General Statistics: *SAS, SPSS*

[2] SIOP posters are peer reviewed based on a 12 page manuscript. The rejection rate is over 50%.