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Prefrontal Cognitive Ability, Intelligence, Big Five Personality, and the Prediction of Advanced Academic and Workplace Performance

Daniel M. Higgins
Harvard University

Jordan B. Peterson
University of Toronto

Robert O. Pihl
McGill University

Alice G. M. Lee
University of Hawai'i at Manoa

Studies 1 and 2 assessed performance on a battery of dorsolateral prefrontal cognitive ability (D-PFCA) tests, personality, psychometric intelligence, and academic performance (AP) in 2 undergraduate samples. In Studies 1 and 2, AP was correlated with D-PFCA ($r = .37$, $p < .01$, and $r = .33$, $p < .01$, respectively), IQ ($r = .24$, $p < .05$, and $r = .38$, $p < .01$, respectively), and Conscientiousness ($r = .26$, $p < .05$, and $r = .37$, $p < .01$, respectively). D-PFCA remained significant in regression analyses controlling for intelligence (or *g*) and personality. Studies 3 and 4 assessed D-PFCA, personality, and workplace performance among (a) managerial–administrative workers and (b) factory floor workers at a manufacturing company. Prefrontal cognitive ability correlated with supervisor ratings of manager performance at values of r ranging from .42 to .57 ($ps < .001$), depending on experience, and with factory floor performance at $pr = .21$ ($p = .02$), after controlling for experience, age, and education. Conscientiousness correlated with factory floor performance at $r = .23$.

Keywords: dorsolateral prefrontal cortex, academic performance, job performance, personality, intelligence

Intelligence has been most formally described with the "orthodox model" (Eysenck, 1998, p. 108), derived from factor analysis, and conceptualized as a hierarchical structure. At the base of the structure are individual tests of cognitive ability, all of which are positively intercorrelated. These may be arranged at a second stratum into group factors such as fluid intelligence, crystallized intelligence, and visual perception (Carroll, 1993, pp. 624–625). These group factors share a large single domain of variance, *g*, uppermost in the hierarchy (Brand, 1996; Brody, 1992; Carroll, 1993; Jensen, 1998). The general factor *g* accounts for 50%–80% of the variance of the group factors (Deary, 2001) and is associated with a variety of real-world outcomes (Gottfredson, 1997; Herrnstein & Murray, 1994; Schmidt & Hunter, 1998). The orthodox model has generated a number of key empirical findings (Neisser et al., 1996) and provides the bulk of nonfolk understanding of the consequences and biological–brain correlates of intelligence (Jensen, 1998). Intelligence is importantly related to everyday competence (Gottfredson, 1997), academic performance (Brody, 1992; Neisser et al., 1996), job performance (Schmidt & Hunter, 1998), and various other important social outcomes (Herrnstein & Murray, 1994; Jensen, 1998). IQ has been associated with brain size (Anderson, 2003), and nerve conduction velocity appears associated with IQ for primary heritable reasons (Rijsdijk & Boomsba, 1997). Reliable correlations have been reported between IQ and various elementary cognitive tasks. IQ has been correlated with simple reaction time, for example, at −.10; with choice reaction time at −.30; and with inspection time at −.40 (Deary, 2000; Jensen, 1998). Finally, the heritability of general intelligence approximates .50–.80 (Plomin, 2001).

Although it is difficult to overstate the success of the collaborative program of psychometric intelligence research that has played out over the past century (Jensen, 1998), there remain several problems in the general domain of cognitive ability and performance that are, as yet, unresolved by the psychometric approach. First and foremost is the formal nature of the psychometric conception of intelligence (the hierarchical factor analytic model), suspended, as it were, in rarefied air because of its complex statistical definition and limited grounding in other domains of psychology and neuroscience (Deary, 2000). Ian Deary (2000)

Daniel M. Higgins, Department of Psychology, Harvard University; Jordan B. Peterson, Department of Psychology, University of Toronto, Toronto, Ontario, Canada; Robert O. Pihl, Department of Psychology, McGill University, Montreal, Quebec, Canada; Alice G. M. Lee, Faculty of Medicine, University of Hawai'i at Manoa.

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Correspondence concerning this article should be addressed to Jordan B. Peterson, Department of Psychology, University of Toronto, 100 St. George Street, Toronto, Ontario, Canada M5S 3G3. E-mail: jordanbpeterson@yahoo.com

has argued that what some researchers may take as the psychometric "theory" of human intelligence, the "three-stratum theory," is not so much a scientific theory as it is a statistical procedure for reliably identifying consistent "pools of inter-individual variability in the performance of mental tasks" across data sets (p 17), and has reminded scientists that they still lack an adequate psychological theory to account for the remarkable empirical regularity represented by the hierarchical model.

The second central issue is the practical prediction of performance. The use of cognitive ability to predict academic and job performance is an important aspect of classical psychometrics, educational psychology, and organizational psychology (Neisser et al., 1996). However, an optimized combination of IQ and other trait measures (e.g., personality traits) still leaves 60%–75% of the variance in performance unaccounted for (Schmidt & Hunter, 1998), and even small increments in predictive validity, with regard to performance prediction, can have substantial practical (Rosenthal, 1990) and economic consequences (Schmidt & Hunter, 1998). Furthermore, a number of researchers have suggested that standard IQ tests are limited: They evolved specifically to assess the ability to solve well-defined (academic) problems and therefore do a rather poor job of assessing an individual's ability to solve ill-defined problems (Pretz, Naples, & Sternberg, 2003). Robert Sternberg's (1999) theory of practical intelligence represents an essentially psychometric attempt to capitalize on this distinction. Unfortunately, so far, this work has not been transformed into effective technologies of assessment or intervention (Gottfredson, 2003, p. 343; but see Sternberg's, 2003, reply).

If one takes a neuropsychological rather than a psychometric approach to intelligence, one finds the problem conceptualized at a variety of levels of sophistication. Perhaps the crudest idea in all of psychology—that smart people have bigger brains—has evolved from its earliest mode of measuring cranial capacity with lead shot (Gould, 1996), through statistical correlation of intelligence with head size (Jensen, 1994), to meta-analytic studies of magnetic-resonance-imaging-based estimates of brain volume correlations with intelligence (Anderson, 2003; McDaniel, 2005). From a functional perspective, intelligence has been associated with neural efficiency based on electroencephalography (EEG; Neubauer & Fink, 2003; Neubauer, Grabner, Fink, & Neuper, 2005; Neubauer, Grabner, Freudenthaler, Beckmann, & Guthke, 2004) and positron emission tomography (PET) studies (Haier, 2003). This global whole-brain approach has recently given way to a series of more anatomically specific, often theory-driven, brain imaging studies. Anatomically, evidence has accrued suggesting that although both grey and white matter volume is correlated with intelligence (Gignac, Vernon, & Wickett, 2003), the association of grey matter volume with intelligence is particularly high in the frontal lobe (Haier, Jung, Yeo, Head, & Alkire, 2004). It appears that this association may be genetically mediated (Toga & Thompson, 2005).

Functional studies (Duncan et al., 2000; J. R. Gray, Chabris, & Braver, 2003; Prabhakaran, Rypma, & Gabrieli, 2001; Prabhakaran, Smith, Desmond, Glover, & Gabrieli, 1997) have also implicated the importance of the prefrontal cortex, along with posterior cortical regions, in solving classes of problems that might be broadly classified as reflecting fluid intelligence (Blair, 2006). This seems reasonable, from a performance-prediction standpoint, as the challenges raised by practical problems are typically delegated, theoretically, to the executive functions of the frontal lobes (Fuster, 1997; Luria, 1980). Indeed, attempts to understand the higher order cognitive processes associated with the prefrontal cortex appear particularly relevant to augmenting an understanding of intelligence (Duncan, 1995). If real-world success is conceptualized as long-range goal framing and attainment, intelligence might be viewed as effective goal-directed problem solving under novel and ambiguous environmental circumstances. This notion is consistent with Gardner's (1993) and Sternberg's (1999) ideas and has been elaborated in cognitive (G. A. Miller, Eugene, & Pribram, 1960; Wiener, 1961), social-personality (Carver & Scheier, 1998) and neuroscience-based theories (J. A. Gray & McNaughton, 2000; Peterson, 1999; Rolls, 1999).

More specifically, Duncan (1995) argued that adaptive action involves the planning and execution of hierarchically arranged goals and subgoals (Schank & Abelson, 1977; Wiener, 1961) and believes that the highest level of that hierarchy is governed by the dorsolateral prefrontal cortex (Duncan et al., 2000). Duncan posited that environmental ambiguity (context) or distracted attention (e.g., dual-task interference) reduces the efficiency of the goal-weighting process and leads to goal neglect and impaired behavioral selection or choice. In this view, the weighting process is believed to be particularly sensitive to prefrontal damage and to variance in psychometric *g*. Duncan and his colleagues have demonstrated that goal neglect (disregarding task requirements) can be induced using dual-task interference and that such executive failures characterizes patients with frontal lobe damage and normal participants from the lower end of the *g* distribution (Duncan, Emslie, Williams, Johnson, & Freer, 1996). Duncan et al. (2000) empirically underscored the importance of the prefrontal cortex for (fluid) intelligence with the finding that increased lateral frontal activation (using PET) is associated with solving heavily *g*-loaded problems but not with solving problems whose *g* loadings are negligible. In short, Duncan has argued that *g* is the reflection of the cognitive process of the dorsolateral prefrontal cortex in psychometric space. These technologically driven advances have created a new wave of optimism that the neurobiological basis of Spearman's *g* will soon be elucidated (Blair, 2006; J. R. Gray & Thompson, 2004), although this optimism is not universal (Carey, 2005).

This new wave of neuroscientific investigation into psychometric intelligence is supported on its cognitive–psychological flank by a theoretical reconceptualization of intelligence in terms of Cattell's (1987) distinction between crystallized and fluid intelligence (Blair, 2006; Duncan et al., 2000; J. R. Gray et al., 2003). The key cognitive component of this view of fluid intelligence is working memory (Blair, 2006; Duncan, 2005; J. R. Gray & Thompson, 2004). Empirical work crystallized around an early confirmatory factor analytic study of working memory by Kyllonen and Christal (1990). This study suggested that the common factor underlying working memory ability might be virtually indistinguishable from reasoning ability, which they explicitly characterized as *general fluid intelligence*. The idea that prefrontally mediated working memory plays a determining role in fluid intelligence (Kane & Engle, 2002) has been reinforced by a series of recent studies from several groups (Ackerman, Beier, & Boyle, 2002; Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Conway, Kane, & Engle, 2003; Kane et al., 2004; Süβ, Oberauer, Wittmann, Wilhelm, & Schulze, 2002) demonstrating a strong association between working memory and (fluid) intelligence.

Indeed, the empirical (Kane, Hambrick, & Conway, 2005; Oberauer, Schulze, Wilhelm, & Süβ, 2005) and conceptual (Deary, 2000) overlap between working memory and psychometric intelligence is so striking that researchers have had to take considerable pains to argue that they are distinct constructs (Blair, 2006). On the basis of a recent meta-analysis, Ackerman, Beier, and Boyle (2005) suggested that the correlation between working memory capacity and psychometric *g* approximates .48, and in a manner quite uncharacteristic of this new assault on psychometric intelligence, they suggested a psychometric interpretation of working memory capacity as a lower order cognitive ability in the standard hierarchical model of intelligence (Carroll, 1993). In a critical response to the Ackerman et al. article, both Kane et al. (2005) and Oberauer et al. (2005) offered meta-analytically derived correlations between psychometric *g* and working memory that are substantially higher (.85 and .72, respectively) while strongly asserting their conceptual distinction. Oberauer et al. (2005) even suggested that interpreting working memory capacity in terms of the psychometric model of intelligence is inappropriate. They suggested that such an interpretation reflects a conceptual misunderstanding of the working memory construct, and the scientific advances researchers have made in understanding its construct validity (Conway et al., 2005), its neural underpinnings (Blair, 2006; Duncan, 2005; Fuster, 2005; Kane & Engle, 2002), and its consequent potential to advance understanding of the inscrutable psychometric construct of general intelligence (J. R. Gray & Thompson, 2004).

In general, then, cognitive neuroscientists have come to provisionally understand intelligence in terms of cognitive processes associated with the prefrontal cortex (Duncan, 2005; Fuster, 2005; J. R. Gray & Thompson, 2004). Unfortunately, this work still remains poorly integrated with the larger body of knowledge derived from over 100 years of psychometric research, and much remains to be gained from a fully bipartisan psychometric–cognitive-neuroscientific approach (Deary, 2005). First is the issue of convergent and divergent validation:

> When neuropsychologists devise and name a test of mental function, they can profit from the psychometric approach which construes people's performance on the test in terms of variance shared with other tests (whether this is at the *g* or group factors level) and variance specific to that test itself. (Deary, 2005, p. 227)

Then there is the equally important and interesting question of criterion validity. Prefrontally mediated cognitive processes, including working memory, may very well share substantial variance with psychometric intelligence. This leaves open the question of whether these prefrontal cognitive processes share substantial variance with the important life outcomes (e.g., academic performance, job performance, social status, etc.) that make the investigation of psychometric intelligence relevant in the first place (Herrnstein & Murray, 1994).

Whereas the work described above could be characterized as an attempt to account for individual differences in psychometric intelligence in terms of neuropsychological constructs using the methods of cognitive neuroscience, the work presented in this article could be described as an attempt to define cognitive processes associated with the prefrontal cortex in psychometric terms. To this end, we operationally defined dorsolateral prefrontal cognitive ability (D-PFCA) as performance on a computerized battery of prefrontal cognitive tasks, established its psychometric properties and examined its relationship to psychometric intelligence and academic and job performance. Furthermore, because of its demonstrated relevance to performance prediction (Hunter & Schmidt, 1996), Big Five personality assessment was also incorporated into these studies. The Big Five constitute a well-defined measurement model for assessing personality across five broad dimensions: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness (Digman, 1990; L. R. Goldberg, 1992; John & Srivastava, 1999). The personality dimensions assessed by this five-factor model appear valid cross-culturally (McCrae & Costa, 1997) and are substantially heritable (Loehlin, McCrae, Costa, & John, 1998) and relatively stable across the life span (Costa & McCrae, 1997). Conscientiousness, in particular, has broad predictive validity for academic (Goff & Ackerman, 1992; E. K. Gray & Watson, 2002; M. G. Rothstein, Paunonen, Rush, & King, 1994) and job performance (Barrick & Mount, 1991; Hogan, Hogan, & Roberts, 1996; Hunter & Schmidt, 1996; Hurtz & Donovan, 2000; Salgado, 1997).

The first two studies presented in this article examined the relationship between D-PFCA, psychometric intelligence, Big Five personality, and achievement in higher academic settings. The second two studies, which did not include measures of psychometric intelligence, extended the assessment of the criterion validity of D-PFCA and personality to the workplace in (a) complex managerial–administrative positions and (b) simpler, rote-learning, assembly-line positions.

STUDY 1

Study 1 had two specific goals: to examine the relationship between D-PFCA and intelligence and to predict academic performance. Predicting academic performance was the original problem of intelligence research, first tackled by Binet and Simon (1905). Grade point average (GPA) has not proven itself a particularly useful predictor of real-world performance (Schmidt & Hunter, 1998), and the distinction between academic intelligence and practical or real-world intelligence has recently been stressed (Sternberg, 1999). However, maintaining a good GPA at a highly competitive university is a complex and multiply determined task, requiring a high level of performance over a protracted period of time, as well as mastery across a range of domains. In addition, for much of this assessment period, the student inhabits a rapidly changing environment and, in addition to handling course work, must exercise substantial executive control over a novel and complex social, athletic, or cultural life. Thus, GPA is neither artificially constrained nor a shallow indicator of performance. Finally, because GPA reflects performance averaged across many occasions, raters, and contexts, it provides a standard and well-defined measure of performance, whose apparent psychometric properties are very difficult to duplicate in putative real world investigations. In consequence, the first study examined the differential validity of D-PFCA, IQ, and Scholastic Aptitude Test (SAT) scores with regard to the prediction of academic performance. Because of the apparent multiple determination of academic performance, the study also assessed Big Five personality. The trait of Conscientiousness appears most relevant to the current discussion, as this trait has consistently emerged as a predictor of academic and job performance. We hypothesized that D-PFCA would predict IQ and SAT scores. Furthermore, we explored the possibility that D-PFCA would predict academic performance over and above IQ and SAT. Finally, we hypothesized that Conscientiousness would independently predict academic performance.

Method

Participants

Participants in this study included 121 full-time undergraduates in the Faculty of Arts and Science at Harvard University, Cambridge, Massachusetts. All participants were enrolled in an introductory course in personality psychology and received course credit in return for participation. Although participation was optional, all students enrolled in the course completed the experiment. The participants included 67 female students. The average age of the participants was 20 years (n = 117, SD = 1.4 years, range: 18–24 years). Age data were unavailable for three participants. One older student (age = 28 years) was excluded from the calculation of average age.

Materials

Dorsolateral Prefrontal Cognitive Tasks

We defined D-PFCA as performance on a computerized battery of seven neuropsychological tasks. Originally derived from clinical neuropsychological studies (Milner & Petrides, 1984; Milner, Petrides, & Smith, 1985), these tasks have been associated as specifically as possible with dorsolateral prefrontal cortical function, as evidenced by a minimum of one well-designed clinical study of brain-damaged patients, lesion studies with nonhuman primates, and neuroimaging studies of non-brain-damaged people. Performance on these tasks has variously been associated with alcoholic propensity (Peterson, Finn, & Pihl, 1992), alcohol-related aggression (Lau, Pihl, & Peterson, 1995), physical aggressiveness in boys (Séguin, Nagin, Assaad, & Tremblay, 2004; Séguin, Pihl, Harden, Tremblay, & Boulerice, 1995), and school performance (Peterson, Pihl, Higgins, Séguin, & Tremblay, 2003). Administration of the battery, which includes the following tasks, requires approximately 90 min.

Conditional associative learning: Introduction. Petrides (1985b, 1987) designed two conditional associative tasks to demonstrate that the deficits seen in delayed response tasks in monkeys with frontal damage may reflect an inability to learn conditional behavioral rules (if Cue A, then Response X; else, if Cue B, Response Y) rather than a working memory deficit. In the rhesus monkey, periarcuate lesions (Area 8, Rostral Area 6), but not periprincipalis lesions, produce impairments on both spatial (Petrides, 1987) and nonspatial (Petrides, 1982, 1985a) conditional associative tasks. In humans, unilateral surgical excisions (for the treatment of epilepsy) of the left or right frontal lobes produce impairments on both the spatial (Petrides, 1985b) and nonspatial (Petrides, 1985b, 1990) versions of this task. Using PET, Petrides, Alivisatos, Evans, and Meyer (1993) also found selective activation in Area 8 of the left frontal cortex during performance of the nonspatial version of this task. A symmetrically reinforced go/no-go task may also be conceptualized as a conditional task, with correct performance dependant on mastery of a conditional rule: If X, go; else, if Y, do not go (Petrides, 1987). As with the conditional associative tasks, monkeys with periarcuate lesions are impaired on this go/no-go task relative to monkeys with periprincipalis lesions and normal controls (Petrides, 1986, 1987).

1. Spatial conditional associative task. The participant is presented with five identical circles and five identical squares arranged in a fixed spatial array. The participant is instructed that each square is associated with exactly one circle. On each trial, a circle is highlighted, and the participant is required to click the square he or she believes might be associated with that circle. If the participant chooses the correct square, the word "Correct" appears on the screen, the trial is scored as correct, and the next trial begins. If the participant chooses an incorrect square, the word "Wrong" appears on the screen, the trial is scored as incorrect, and the participant is allowed to continue to guess until he chooses the correct square. Only when the participant clicks the correct square does the next trial begin. The task is terminated when the participant completes 10 consecutive correct trials or completes 100 trials, whichever comes first. The participant completes two different versions of this task (differing in the spatial arrangement of the shapes) and receives a raw score equal to the total number of trials completed across both versions.

2. Nonspatial conditional associative task. This task is similar to the spatial version except that the spatial aspect has been removed. The participant is explicitly required learn arbitrary associations between cue words and target words. There are five cue words and five target words. The participant is instructed that each cue word is associated with exactly one of the target words. On each trial, the participant is presented with a cue word (in the center of the screen) and all five target words (arranged in a circle around the cue word). The relative position of each of the target words varies randomly from trial to trial. The participant is instructed to click the target word he or she believes might be associated with the cue word. If the participant chooses the correct target word, the word "Correct" appears on the screen, the trial is scored as correct, and the next trial begins. If the participant chooses an incorrect target word, the word "Wrong" appears on the screen, the trial is scored as incorrect, and the participant is allowed to continue to guess until he or she selects the correct word. Only after clicking the correct word does the next trial begin. The task is terminated when the participant completes 10 consecutive correct trials or completes 100 trials, whichever comes first. The participant completes two different versions of this task (the first employs regular words, whereas the second uses nonwords [e.g., *egtao*]) and receives a raw score equal to the total number of trials completed across both versions.

3. Go/no-go. The participant is presented with four stimuli (letters) flashing sequentially, repeatedly, and in random order on the screen. Each appearance of a letter constitutes a trial. The letters are displayed for 2 s. The intertrial time is a Gaussian-distributed random number with a mean of 600 ms and a standard deviation of 300 ms. Two of the letters are go stimuli, and two are no-go stimuli. The participant is told that he or she should click when certain letters appear and not click when others appear. Whenever the participant makes a correct response (clicking on a go trial or not clicking on a no-go trial), he or she is rewarded by the appearance of the word "Good" and by an increase in his or her score by 1 point (the score is displayed throughout the task). The task is terminated after 200 trials or after 20 consecutive correct trials. The raw (error) score is the number of trials completed.

Working memory: Introduction. Patients with unilateral left and right frontal lobe surgical excisions perform poorly on the self-ordered pointing task relative to brain-damaged and normal controls (Petrides & Milner, 1982; Wiegersma, van der Scheer, & Human, 1990). In monkeys, this deficit appears to be specific to mid-dorsolateral frontal cortex (Areas 9 and 46), rather than the more posterior dorsolateral cortex (Areas 6 and 8; Petrides, 1995b). PET has identified activation foci in Areas 46 and 9 in (normal) humans while performing this task (Petrides, Alivisatos, Evans, & Meyer, 1993). Patients with frontal lobe lesions also appear impaired on an analogous verbal working memory task, the digit span randomization task (Wiegersma et al., 1990). Once again, PET has revealed bilateral activation in mid-dorsolateral frontal cortex, Areas 46 and 9 (Petrides, Alivisatos, Meyer, & Evans, 1993). Finally, frontal lobe damage also appears associated with poor performance on a recency discrimination task (Milner et al., 1985). When presented with a series of concrete representational drawings or abstract figures, for example, patients with unilateral right frontal lobe damage appear impaired relative to normal and brain-damaged controls. When words are used instead of pictures, both left and right frontal damage is associated with poor performance.

Petrides (1989, 1995a, 1998, 2000) argued that all these tasks reflect the importance of the frontal cortex for working memory. According to his two-level hypothesis, ventrolateral frontal cortex interacts with temporal and parietal association areas and mediates encoding and retrieval of information in short-term and long-term memory. The mid-dorsolateral frontal cortex, on the other hand, is responsible for the simultaneous manipulation and monitoring of multiple pieces of information in working memory (Petrides, 1998). Areas 46 and 9 appear critically involved in this latter function, and performance on the self-ordered, randomization, and recency discrimination tasks reflects the activity of this mid-dorsolateral memory system (Petrides, 1989).

4. Self-ordered pointing task. The participant is presented with 12 stimuli and instructed to click on each stimulus exactly once. There is no time limit. After each trial (or selection), the spatial location of each stimulus immediately changes, thus removing any spatial aspect of the task. The participant is allowed to make only 12 selections. The participant completes four version of the task, each using different classes of stimuli: abstract figure pictures, pictures of easily named objects, words, and nonwords (e.g., *xworl*). The raw score for this task is the number of distinct stimuli selected across all four versions (i.e., 48 − number of errors).

5. Randomization task. For each trial, the participant is asked to input a random sequence of letters for a given letter span (e.g., participants were asked to "randomize the letters from L to O," i.e., a four-letter span). The participant enters letters by using the computer monitor and the mouse. The monitor shows one of the letters from the letter span. If the participant moves the mouse (in any direction), the letter will change. As the participant continues to move the mouse, new letters are displayed. While the mouse is moving, the display will cycle forward through all the letters in the span, beginning again at the first letter after the last letter has been displayed. To select a letter, the participant clicks the mouse button while the letter is on the screen. If the participant produces an acceptable sequence, he or she is asked to randomize a span one letter longer than the previous span. If the participant makes an error (omission or patterned sequence, e.g., L, M, N), he or she is given a second chance to randomize a span of the same length. Before beginning the task proper, the participant must successfully randomize 2 four-letter-span practice trials. After this, the participant begins the scored trials with a letter span of four. The task terminates when the participant fails to randomize a given length span two trials in a row or when he or she correctly completes all trials (span length 4–14). The raw score is the maximum length of span successfully randomized.

6. Recency discrimination task. On a typical trial, the participant is sequentially presented with a series of (either six or eight) familiar nouns. Each word appears for 800 ms and is followed by a delay of 100 ms before the next appears. After all the words in the sequence have been presented, the participant is shown two words from the sequence and asked to "click on the word that appeared most recently." The participant completes eight trials with six words and 14 trials with eight words. The raw score is the number of trials for which the participant correctly identified the more recent word.

Word fluency: Introduction. Both Milner and Benton (reviewed in Damasio & Anderson, 1993, p. 435) have demonstrated that patients with left (but not right) frontal lobe damage manifest impairment on Thurstone's Word Fluency Test without presenting with typical aphasia. Although patients with left frontal damage are impaired on a word fluency task, both left and, more particularly, right frontal damage appears associated with deficits on a design fluency task (Milner & Petrides, 1984). PET studies have demonstrated increased activation in left dorsolateral prefrontal cortex in normal participants while performing a verbal fluency task (Frith, Friston, Liddle, & Frackowiak, 1991) and that the level of bilateral frontal lobe activity measured during a resting state scan is negatively correlated with the number of words produced (Boivin et al., 1992).

7. Word fluency task. The participant is instructed to enter as many words as possible beginning with *ST*. He or she is instructed not to use inflected forms and is given 5 min to complete the task. The participant enters words by clicking an on-screen keyboard using the mouse. The letters on this keyboard are arranged in alphabetical order, and letters appear on the screen as they are selected. The raw score is the number of valid words entered.

D-PFCA scoring. A sample of 444 participants was used to establish scaled scores for each task. The scaled scores were standardized normal scores (Anastasi & Urbina, 1997), determined by calculating a percentile rank for each participant (based on raw scores) and computing the z-score equivalent (based on the inverse probability function) of this percentile rank. This resulted in a raw score to (z-score equivalent) scale score mapping. In this standard sample of 444, the average intercorrelation among the dorsolateral prefrontal cognitive tasks (scaled scores) was .27. The internal consistency reliability coefficient, or coefficient α, for these tests, when taken as a composite, was .72. An aggregate dorsolateral prefrontal cognitive performance score, D-PFCA, was calculated for each participant as the average of the scaled scores across the seven dorsolateral prefrontal cognitive tasks.

IQ

A short form of the Wechsler Adult Intelligence Scale—Revised (WAIS–R; Wechsler, 1981) consisting of the block design and vocabulary subtests was used to measure IQ. With validity and reliability defined as per Tellegen and Briggs (1967), this is the most valid (part–whole correlation) and reliable (inter- and intratest reliability) two-subtest short form of the WAIS–R (Cyr & Brooker, 1984; Silverstein, 1982). The validity coefficient for this short form is .90, whereas the reliability coefficient is .94 (Ward & Ryan, 1996). Full scale equivalent IQ scores (IQ) were calculated according to Brooker and Cyr (1986). The national mean for WAIS–R IQ is 100 and the standard deviation 15 (Wechsler, 1981).

Personality

The 240-item Revised NEO Personality Inventory (NEO-PI-R) Form S (Costa & McCrae, 1992) was used to assess personality. This scale measures the personality dimensions of Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness, and the subscales have reliability coefficients of .92, .89, .87, .86, and .90, respectively.

Grades

Official university transcripts were available for 72 participants. The transcripts included a cumulative ranking, which is a number from 1 to 6: a score of 1 reflecting higher academic performance than 6. A variable, GRADES, was calculated as 7 − cumulative ranking, resulting in a GRADES score from 1 to 6 points. Year 1 rankings were available for 72 participants, whereas Years 2, 3, and 4 were available for 48, 28, and 15 participants, respectively. Coefficient α was calculated on the basis of the correlation between Year 1 ranking and the average of the rankings across Years 2–4. When calculated this way, coefficient α for the GRADES composite used in this study was .84 ($n = 48$). Only one participant scored 1 point. This was an extreme value, and the participant was removed from any subsequent analysis involving GRADES.

Demographics

The participants completed a demographics questionnaire, in which they were asked to rate their family's annual gross income on a scale of 1 to 13, where 1 = $1,000–$10,000; 2 = $10,000–$20,000; 3 = $20,000–$30,000; 4 = $30,000–$40,000; 5 = $40,000–$50,000; 6 = $50,000–$75,000; 7 = $75,000–$100,000; 8 = $100,000–$150,000; 9 = $150,000–$500,000; 10 = $500,000–$1,000,000; 11 = $1,000,000–$5,000,000; 12 = $5,000,000–$10,000,000; 13 = $10,000,000 or more. This annual household income index (AHII) was used as a control variable in some of the analyses reported below.

Scholastic Aptitude Test

The SAT has two subtests, a verbal subtest (SAT-V) that tests reading comprehension, antonyms, analogies, and sentence completion and a mathematical subtest (SAT-M) that focuses on numerical and quantitative ability. These subtests are standardized to a national mean of 500 and standard deviation of 100 (Jensen, 1980, p. 483). Participants were asked to enter their best SAT-V score and their best SAT-M score on the demographics questionnaire.[1]

Procedure

During the course of the semester, participants completed the NEO-PI-R and the demographics questionnaire at home at a time of their choosing. A trained tester administered the two WAIS–R subtests in the laboratory. On a separate day, participants came into the laboratory to complete the computerized battery of dorsolateral prefrontal cognitive tasks. Official transcripts were obtained from the registrar's office, with the student's written permission.

Results

Personality

Descriptive statistics and intercorrelations for NEO-PI-R personality factors and GRADES are presented in Table 1. Conscientiousness was the only personality variable that was significantly correlated with GRADES. Openness was significantly correlated with IQ ($r = .28$, $n = 106$, $p = .004$, two-tailed) and SAT-V ($r = .29$, $n = 114$, $p = .001$, two-tailed). These were the only significant correlations between the five personality factors and the cognitive variables (IQ, SAT-V, SAT-M, D-PFCA).

Cognitive Variables

Descriptive statistics and intercorrelations for D-PFCA, IQ, SAT-V, SAT-M, AHII, and GRADES are presented in Table 2. All the cognitive variables were positively intercorrelated, and each was significantly positively correlated with GRADES. The zero-order correlations of AHII with the cognitive variables and GRADES were not significant (unlike Study 2, below).

D-PFCA Predicts Academic Performance After Controlling for IQ and SAT Scores

The results of a standard multiple regression, with GRADES as the dependent variable and D-PFCA, IQ, SAT-V, SAT-M, Conscientiousness, and AHII as independents, are presented in Table 3. The regression coefficients for D-PFCA, SAT-V, Conscien-

[1] Because these self-reported SAT scores were used in the subsequent analyses, a few comments regarding their probable accuracy are appropriate. Participants were assigned a numeric ID code and were required to use this code (rather than their true identity) for all aspects of the experiment. Thus, they were aware that their true identity would not be associated with the SAT scores they provided. In all, 115 participants provided their SAT scores. Of these, 109 (95%) explicitly stated that the scores were accurate, and 79 (69%) explicitly stated that they would be willing to provide hard copies of their SAT reports (using their assigned numeric ID codes). Before providing their official transcripts, participants were asked to rate their academic performance on a scale of 1 to 12: 1 = A (4.00), 2 = A− (3.67), 3 = B+ (3.33), 4 = B (3.00), 5 = B− (2.67), 6 = C+ (2.33), 7 = C (2.00), 8 = C− (1.67), 9 = D+ (1.33), 10 = D (1.00), 11 = D− (0.67), and 12 = *F*(0.00). This self-report rating of academic performance correlated with the cumulative rankings from the official transcript (which is on a scale of 1–6, i.e., quite different from the self-report scale) at $r = .88$ ($n = 71$, $p < .001$, one-tailed). Thus, participants' self-report academic performance matched their official transcript ranking quite closely. Taken together, these facts support the validity of the self-report SAT scores.

Table 1
Descriptive Statistics and Intercorrelations for Revised NEO Personality Inventory Personality Factors and Academic Performance for Studies 1 and 2

Variable	*M*	*SD*	Range	1	2	3	4	5	6
Study 1 (N = 117)									
1. N	99.86	24.37	42–157	—					
2. E	115.85	21.78	66–168	−.38**	—				
3. O	130.05	19.62	71–173	.15	.20*	—			
4. A	111.79	21.78	59–168	−.01	.15	.30**	—		
5. C	105.50	23.26	57–157	−.49**	.26**	−.18	.09	—	
6. GRADES[a]	4.77	0.74	3–6	.03	.18	.17	.13	.26*	—
Study 2 (N = 141)									
1. N	100.21	25.58	50–171	—					
2. E	117.09	21.33	56–174	−.33**	—				
3. O	132.38	19.18	78–170	−.12	.43**	—			
4. A	113.64	18.73	40–158	−.30**	.10	.22**	—		
5. C	109.81	22.08	46–164	−.44**	.10	−.04	.23**	—	
6. GRADES[b]	2.93	0.60	1.29–4.12	−.03	−.05	.09	.07	.37**	—

Note. N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness; GRADES = academic performance.
[a] $N = 70$ for this variable because of missing data and removal of one extreme value. [b] $N = 133$ for this variable because of missing data.
* $p < .05$, two-tailed. ** $p < .01$, two-tailed.

tiousness, and AHII were significant (one-tailed tests), whereas those for IQ and SAT-M were not.

Two additional regression analyses were run to compare the traditional means of predicting academic performance (IQ, SAT-V, and SAT-M) with D-PFCA and Conscientiousness. When GRADES was regressed on IQ, SAT-V, and SAT-M, the *R* for regression was .39, $F(3, 62) = 3.62$, $p = .02$, and the adjusted R^2 was .11. On the other hand, when GRADES was regressed on PFCA and Conscientiousness, *R* for regression was .48, $F(2, 65) = 9.59$, $p < .001$, and the adjusted R^2 was .20. In this latter regression, the standardized regression coefficients (βs) were .41 and .31 for D-PFCA and Conscientiousness, respectively.

Table 2
Descriptive Statistics and Intercorrelations for Cognitive Measures, Academic Performance, and Annual Household Income for Studies 1 and 2

	Descriptive statistics				Correlations							Sample size for correlations						
Variable	*N*	*M*	*SD*	Range	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Study 1																		
1. GRADES	71	4.77	0.74	3–6	—							—						
2. D-PFCA	110	0.47	0.48	−0.91–1.83	.37**	—						69	—					
3. AHII	118	7.59	1.85	2–13	.08	−.01	—					70	107	—				
4. IQ	109	127.61	11.48	100–151	.24*	.20*	.05	—				67	102	107	—			
5. RPM	—	—	—	—	—	—	—	—	—			—	—	—	—	—		
6. SAT-V	115	709.57	70.19	530–800	.35**	.21*	.04	.57**	—	—		69	105	115	106	—	—	
7. SAT-M	115	727.74	55.28	560–800	.33**	.39**	−.07	.34**	—	.41**	—	69	105	115	106	—	115	—
Study 2																		
1. GRADES	133	2.93	0.60	1.29–4.12	—							—						
2. D-PFCA	142	0.08	0.47	−1.29–1.30	.33**	—						133	—					
3. AHII	142	6.63	1.86	2–13	.20*	.17*	—					133	142	—				
4. IQ	142	126.85	13.92	98–155	.39**	.45**	.30**	—				133	142	142	—			
5. RPM	142	25.3	4.33	13–35	.18*	.50**	.17*	.57**	—			133	142	142	142	—		
6. SAT-V	142	—	—	—	—	—	—	—	—	—		—	—	—	—	—	—	
7. SAT-M	142	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

Note. AHII = Annual Household Income Index; D-PFCA = dorsolateral prefrontal cognitive ability; GRADES = academic performance; RPM = Raven's Advanced Progressive Matrices, Set II; SAT-M = mathematical score on Scholastic Aptitude Test; SAT-V = verbal score on Scholastic Aptitude Test.
* $p < .05$, one-tailed. ** $p < .01$, one-tailed.

Table 3
Regression Analyses Predicting Academic Performance With D-PFCA, IQ, g, SAT, Conscientiousness, and AHII for Studies 1 and 2

Variable	*B*	*SE B*	β	*t*	p^a	*r*	*pr*	*sr*	Regression
Study 1: Regression of GRADES on IQ, SAT-V, SAT-M, D-PFCA, C, and AHII									
Constant	0.009	1.405		0.01	.995				$R = .59$
IQ	0.001	0.009	.02	0.17	.865	.24	.02	.02	$R^2 = .34$
SAT-V	0.003	0.001	.24	1.82	.073	.31	.23	.20	adjusted $R^2 = .27$
SAT-M	0.001	0.002	.05	0.40	.692	.33	.05	.04	$F(6, 57) = 4.96$, $p < .001$
D-PFCA	0.546	0.178	.37	3.07	.003	.36	.38	.33	
C	0.012	0.004	.33	3.02	.004	.28	.37	.32	
AHII	0.082	0.049	.18	1.69	.097	.11	.22	.18	
Study 2: Regression of GRADES on IQ, D-PFCA, C, and AHII									
Constant	0.456	0.503		0.91	.367				$R = .53$
IQ	0.010	0.004	.24	2.68	.008	.40	.23	.20	$R^2 = .29$
D-PFCA	0.216	0.108	.17	2.01	.047	.33	.18	.15	adjusted $R^2 = .26$
C	0.008	0.002	.31	4.10	.000	.37	.34	.31	$F(4, 127) = 12.68$,
AHII	0.032	0.026	.10	1.25	.214	.20	.11	.09	$p < .001$
Study 2: Regression of GRADES on *g*, D-PFCA, C, and AHII									
Constant	1.676	0.290		5.78	.000				$R = .51$
g	0.111	0.064	.16	1.75	.083	.34	.15	.13	$R^2 = .26$
D-PFCA	0.240	0.114	.19	2.10	.038	.33	.18	.16	adjusted $R^2 = .24$
C	0.009	0.002	.33	4.26	.000	.37	.35	.32	$F(4, 127) = 11.32$,
AHII	0.040	0.026	.12	1.54	.126	.20	.14	.12	$p < .001$

Note. AHII = Annual Household Income Index; C = Revised NEO Personality Inventory Conscientiousness; D-PFCA = dorsolateral prefrontal cognitive ability; *g* = *g* factor scores; GRADES = academic performance; SAT = Scholastic Aptitude Test; SAT-M = mathematical score on SAT; SAT-V = verbal score on SAT.
[a] *p* values are for two-tailed test.

Discussion

D-PFCA was significantly correlated with, but not identical to, IQ and SAT scores. Although all the cognitive variables were related to academic performance, multiple linear regression suggested that D-PFCA may be related to academic performance over and above IQ and SAT scores. Consciousness was also an independent predictor of academic performance.

STUDY 2

Study 2 was designed to replicate and extend the results of Study 1 and to more thoroughly examine the relationship between D-PFCA, intelligence, and academic performance. Because Study 1 only employed two WAIS–R subtests, it may not have included a broad enough range of standard IQ subtests to allow for a comprehensive comparison of IQ and D-PFCA. In Study 2, we measured D-PFCA in tandem with (a) a five-subtest short form of the Wechsler Adult Intelligence Scale—Third Edition (WAIS–III; Wechsler, 1997) IQ and (b) performance on the advanced set of Raven's Progressive Matrices (RPM; Raven, 1998), which is widely considered to be one of the best single measures of *g* (Jensen, 1998). The RPM and WAIS–III subtests were used to derive *g* factor scores. Personality was assessed using the NEO-PI-R. The specific hypotheses for this study were that D-PFCA would relate to IQ and RPM scores, that D-PFCA would predict academic performance, that D-PFCA would predict academic performance over and above IQ or *g* factor scores, and that Conscientiousness would independently predict academic performance.

Method

Participants

The individuals who participated in this study constituted a subset of participants described in another context (DeYoung, Peterson, & Higgins, 2002). The comprehensive sample of 245 University of Toronto (Toronto, Ontario, Canada) students were recruited either through poster advertisements promising native English-speakers $30 Canadian for completing a variety of Web questionnaires and lab tests or through the departmental Introduction to Psychology study pool, which offered course credit in return for completing the experimental protocol. University transcripts and the relevant cognitive data were available for a subset of 177 of these students. Thirty-five of these participants were excluded from the final analysis either because English did not turn out to be their first language or because their academic department or their transcripts did not meet the inclusion criteria detailed below. There were 97 female and 45 male students in the final sample of 142 persons. The mean age of the participants was 20.7 years ($n = 139$, $SD = 2.5$ years, range: 18–35 years). Only 5 participants were over 25 years, whereas 123 participants were between 18 and 22 years. There was no difference in age between male and female participants.

Procedure

Prospective participants were instructed to visit a Web site where, after identifying themselves as University of Toronto undergraduates and indicating that English was their first language, they were allowed to complete a number of questionnaires and schedule an in-lab session. The in-lab portion of the study required participants to complete the battery of D-PFCA tasks described in Study 1, a short form of the WAIS–III (Wechsler, 1997), RPM Set II (Raven, 1998), the NEO-PI-R Form S personality inventory (Costa & McCrae, 1992), and some additional questionnaires. The order of completion of these tasks was counterbalanced across participants to eliminate order effects. Before leaving, participants either signed a release form for their academic transcripts or submitted a printout of their unofficial grade report from the University of Toronto registrar's Web site.

Materials

WAIS–III and RPM

A short form of the WAIS–III (Wechsler, 1997) was used to measure IQ. The short form was composed of three verbal subtests (Vocabulary, Similarities and Arithmetic) and two performance subtests (Digit Symbol and Block Design). Using formulas developed by Tellegen and Briggs (1967) to correct for error contamination, Ward and Ryan (1996) reported that this short form (VASBY, in Ward & Ryan's, 1996, terminology) offers a validity coefficient (part–whole correlation) of .94 and a reliability coefficient of .96, while reducing testing time by 55%–59%. This short form was somewhat overweighted (three out of five tests) toward crystallized intelligence (Cattell, 1987). RPM Set II, a popular test of fluid intelligence, was also administered. The advanced set is appropriate for the differentiation of individuals of superior ability, for example, university undergraduates (Raven, 1998). The 40-min timed version was used. The test–retest reliability coefficient for this test is .91, whereas its split-half reliability coefficient is .83–.87.

Academic Performance

Transcripts were obtained for all participants. There was a surprising amount of variability among the transcripts in terms of departmental affiliation, academic load, and academic performance. Consequently, only students with transcripts from the Faculty of Arts and Science were included in the analyses. Academic performance (GRADES) was calculated as the straight average of the annual GPA (AGPA) across all valid years. A year was considered valid if the student took at least three academic courses in both spring and fall semesters and did not score an F in either semester. On the transcripts, an F is described as "Wholly Inadequate" and indicates performance that is qualitatively below par. The transcripts fail to indicate whether the grade reflects a student's inability to learn the course material or, as is often the case, the occurrence of personal problems that render the student unable to perform at his or her typical level or result in him or her unofficially withdrawing from the course. Because of the qualitatively distinct nature of an F and the probability that this score reflects nonacademic problems, academic years wherein the student scored an F were excluded from the calculation of GRADES. Additionally, summer courses were excluded entirely, so that AGPA was calculated as the GPA for courses taken in the fall and spring semesters only. GRADES, therefore, reflects an average (across academic years) of each student's typical performance (no Fs) in typical courses (fall and spring) while carrying a typical workload (three to five courses per semester). In the final analysis, only 133 of the participants were Faculty of Arts and Science students and had completed at least one academic year that met the valid-year criteria detailed above, and it was this final subset that was used in all analyses pertaining to GRADES.[2]

Determining the reliability of the GRADES composite was complicated by the fact that Year 1 AGPAs were available for 132 participants, whereas Years 2, 3, 4, and 5 AGPAs were available for 70, 33, 10, and 3 participants, respectively. Consequently, coefficient α was calculated on the basis of the correlation between Year 1 AGPA and the average of the AGPAs across Years 2–5. When calculated this way, coefficient α for the GRADES composite used in this study was .82 ($n = 71$).

Demographics

Participants completed a Web questionnaire designed to collect demographic information. Participants were asked to provide their date of birth and gender. They were also asked to estimate their family's annual gross income (Canadian dollars; 1: $1,000–$9,999; 2: $10,000–$19,999; 3: $20,000–$29,999; 4: $30,000–$39,999; 5: $40,000–$49,999; 6: $50,000–$74,999; 7: $75,000–$99,999; 8: $100,000–$149,999; 9: $150,000–$499,999; 10: $500,000–$999,999; 11: $1,000,000–$4,999,999; 12: $5,000,000–$9,999,999; 13: $10,000,000 or more), and were assigned a score (the AHII) between 1 and 13 that corresponded (based on the above list) to the income level indicated by the participant.

Results

Personality

Table 1 shows means, standard deviations, and intercorrelations for the five NEO-PI-R personality factors and their correlations with GRADES. Conscientiousness was the only personality factor that had a significant correlation with GRADES. Openness was significantly correlated with RPM, IQ, and D-PFCA at $r = .22$, .18, and .17, respectively ($p = .01$, .03, .05, two-tailed, respectively; $n = 141$). None of the correlations between the other four personality variables and the three cognitive variables were significant. Household income (AHII) was positively correlated with Extraversion ($r = .24$, $n = 141$, $p = .002$, two-tailed) and with Openness ($r = .20$, $n = 141$, $p = .01$, two-tailed). The partial correlation between AHII and Openness, when controlling for IQ, was $r = .15$ ($df = 138$, $p = .07$, two-tailed).

Cognitive Variables

Descriptive statistics and correlations for IQ, RPM, D-PFCA, GRADES, and AHII are presented in Table 2. IQ, RPM, and

[2] It should be noted here that the correlation between GRADES thus calculated and the transcript cumulative GPA (reflecting a straight average of performance (F or otherwise) across all courses taken across all semesters (fall, spring, and summer) was .98, and substituting cumulative GPA for GRADES in the analyses described in the Results section had a negligible effect on the results obtained.

D-PFCA were all significantly positively intercorrelated, and each was significantly positively correlated with GRADES. In the relevant literature, measures of intelligence are typically reported as being positively correlated with socioeconomic status (Neisser et al., 1996). In this study, AHII was significantly and positively correlated with IQ, RPM, D-PFCA, and GRADES.

D-PFCA Predicts Academic Performance After Controlling for IQ or g

Principle axis factoring was used to calculate *g* factor scores based on RPM scores and the five WAIS–III subtests (Vocabulary, Similarities, Arithmetic, Digit Symbol, and Block Design). The first factor was extracted and factor scores calculated for each participant using the regression method. This factor accounted for 33% of the variance in the correlation matrix. The factor loadings were .74, .70, .60, .57, .48, and .18, for Block Design, RPM, Similarities, Vocabulary, Arithmetic, and Digit Symbol, respectively. The resulting *g* factor scores had a mean of 0, a standard deviation of 0.88, a minimum of −2.33, and a maximum of 1.77. The correlation between D-PFCA and *g* was .53 ($n = 142$, $p < .001$, one-tailed).

Unlike IQ, D-PFCA and Conscientiousness are not traditional predictors of academic performance. It is of some interest, then, to note that when GRADES was regressed against D-PFCA and Conscientiousness, the regression was significant, $F(2, 129) = 18.54$, $p < .001$, and yielded a multiple R of .47 and an adjusted R^2 of .21, with semipartial correlation coefficients of $sr = .29$ for D-PFCA ($p < .001$, one-tailed) and $sr = .34$ for Conscientiousness ($p < .001$, one-tailed).

In Study 1, regression analysis demonstrated that D-PFCA predicts academic performance over and above IQ and SAT scores. In this sample, when GRADES was regressed against IQ, D-PFCA, Conscientiousness, and AHII (see Table 3), the semipartial correlation of D-PFCA with GRADES was significant, replicating D-PFCA's validity independent of IQ. In previous research (Duncan et al., 2000), the dorsolateral prefrontal cortex has been claimed as the neural substrate *g.* When GRADES was regressed against *g* factor scores, D-PFCA, Conscientiousness, and AHII (see Table 3), the semipartial correlation for D-PFCA was significant, as was the semipartial correlation for *g* (one-tailed), indicating that both D-PFCA and *g* were independently related to performance.

Discussion

A significant positive correlation was found between D-PFCA and university-level academic performance, replicating the finding in Study 1 and increasing our confidence that D-PFCA may be as valid a predictor of performance in this context as traditional intelligence tests. Regression analysis revealed that a combination of D-PFCA and Conscientiousness accounted for 21% (adjusted R^2) of the variance in performance. Adding either IQ or *g* to the predictors did not radically alter this result. These latter regressions demonstrate that D-PFCA predicts performance independent of either traditional IQ or factor analytically derived *g* factors scores. Conscientiousness was also significantly and independently correlated with performance.

D-PFCA and the personality trait of Conscientiousness thus emerge as viable alternatives to IQ (and *g*) as predictors of academic performance—which, by virtue of acting as a gatekeeper to the more prestigious occupations, is itself an important life outcome (Brody, 1992; Neisser et al., 1996).

STUDY 3

Having established at least provisional evidence that D-PFCA is characterized by criterion-related validity in relationship to advanced academic performance and by reasonable divergent and convergent validity in relationship to IQ, *g,* and Big Five trait personality, we attempted to extend its validity to the industrial–organizational domain. Different types of jobs can be rank-ordered according to job complexity, and the correlation between job performance and cognitive ability typically increases with complexity (Hunter & Schmidt, 1996; Schmidt & Hunter, 1998). We therefore examined the validity of D-PFCA and personality for predicting job performance for high-complexity administrative jobs (Study 3) and low-complexity factory floor jobs (Study 4) at a midsized U.S. manufacturing corporation. Study 3, as well as Study 4, also employed a novel Big Five personality trait measure designed for distant, rapid computer administration.

We hypothesized that D-PFCA would be positively correlated with job performance for the higher complexity jobs examined in Study 3. We also hypothesized that Conscientiousness and Emotional Stability would prove useful predictors, following the previous research literature.

Method

Participants

Participants included 80 salaried employees from the administrative branch of a midsized manufacturing corporation. This group included 20 employees in administration and sales, 35 in customer service, 13 in secretarial–basic services, and 12 in management. Thirty-six of the participants were female. Age data were available for 49 participants. The average age was 40.4 years ($SD = 9.7$ years, range: 22–64 years). Participants were aware that their supervisors would have access to the testing results.

Materials

Personality

Personality was measured with a short computerized Five-Dimensional Temperament Inventory (FDTI). The FDTI measures Emotional Stability (reverse Neuroticism), Extraversion, Openness, Agreeableness, and Conscientiousness and is modeled after L. R. Goldberg's (1992) list of 100 trait-descriptive adjectives (TDAs). There are 50 items: 10 items for each of the five factors. Each item is a bipolar visual analogue scale. At each pole, there are three adjectives. The adjectives at one pole are drawn from a list of adjectives that load on the positive end of the underlying factor, whereas the adjectives at the opposite pole load on the negative end of the factor. For example, a typical Extraversion item might have *Unadventurous, Shy, Withdrawn* on the left end of the scale and *Active, Daring, Talkative* on the right end of the scale. Above the scale sits the question "What point on the scale best describes you?" To enter his or her response, the participant clicks on the scale using the mouse.

Item responses from 518 participants (298 university undergraduates and 220 corporate employees) were factor analyzed using principal factor analysis with varimax rotation (the same result is obtained if direct oblimin rotation is used). Goldberg's original five factors were recovered, and these were the only factors with eigenvalues greater than one. This confirmed the five-factor structure of the inventory. Using the same sample, coefficient α for the Emotional Stability, Extraversion, Openness, Agreeableness, and Conscientiousness factors were .97, .98, .95, .96, and .98, respectively. The intercorrelations among the five variables are presented in Table 4.

The relationships of the FDTI factors with the NEO-PI-R and Goldberg's TDA factors were previously investigated using a sample of 177 university undergraduates (Lee, Higgins, Peterson, & Pihl, 2001). The FDTI factors of Emotional Stability, Extraversion, Openness, Agreeableness, and Conscientiousness correlate with the NEO-PI-R factors at −.77, .76, .49, .62, and .73 for Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness, respectively, and with Goldberg's TDA factors at .74, .84, .74, .82, and .82 for Emotional Stability, Extraversion, Openness, Agreeableness, and Conscientiousness, respectively. The mean test–retest reliability of the FDTI was .83 ($p < .01$). For the individual factors, the test–retest reliability was found to be .84, .88, .80, .81, and .81 for Emotional Stability, Extraversion, Openness, Agreeableness, and Conscientiousness, respectively.

Supervisor- and Self-Rated Job Performance

The corporation evaluated their employees twice yearly, in April and in November. Each evaluation included twelve 16-point rating scales: quality, quantity, knowledge, versatility, judgment, communications, human relations, professionalism, responsiveness, punctuality, attendance, and overall performance. The employee's immediate supervisor completed this evaluation. The April and November ratings for a given year were both included on the same form, with, for example, the quality rating scale for April immediately above the quality rating scale for November. For this reason, April and November ratings were treated as part of the same scale, and we derived annual performance ratings by averaging the 24 rating scores found on each annual report. Complete annual evaluation forms were available for three years: 1998, 1999, and 2000. We used the Year 2000 evaluations to calculate the internal consistency of the performance rating scale because it included evaluations for the largest subset of participants ($n = 76$). Coefficient α for Year 2000 ratings was .95. In addition to supervisor ratings, the corporate records also included self-rated evaluations. The self-rated forms were identical in format to the supervisor-rated forms. Again, Year 2000 evaluations were used to determine the internal consistency of the self-rated evaluations. Coefficient α for Year 2000 self-rated evaluations was .97 ($n = 73$)

Procedure

Participants completed the FDTI and the computerized D-PFCA battery described in Study 1. All participants were tested privately in a quiet, isolated room. Job performance data were collected from the corporation's internal records.

Results

Performance Ratings

Descriptive statistics and intercorrelations for annual supervisor (1998, 1999, 2000) and self- (1998, 1999, 2000) ratings of job performance are presented in Table 5. The average intercorrelation across the three years was $r_{\text{ave}} = .71$ for supervisor ratings, $r_{\text{ave}} = .72$ for self-ratings, and $r_{\text{ave}} = .64$ for both supervisor ratings and self-ratings. Three composite variables were formed: SUPPERF is the average of the annual supervisor ratings of performance, SELFPERF is the average of the annual self-ratings of performance, and PERF is the average of all annual ratings of job performance. The internal consistencies, coefficient αs, for these composites were .88, .89, and .92 for SUPPERF, SELFPERF, and PERF, respectively.

Personality and Performance

Descriptive statistics and the intercorrelations among personality variables and job performance composites are presented in Table 6, which indicates some disagreement between supervisor-rated and self-rated performance. Supervisor-rated job performance was not significantly correlated with any of the personality variables. Self-rated job performance, on the other hand, was significantly correlated with Extraversion, Openness, and Conscientiousness and had near-significant correlations with Emotional Stability and Agreeableness ($p = .09, .10$, two-tailed, respectively).

Table 4
Descriptive Statistics and Intercorrelations Among Five-Dimensional Temperament Inventory Factors for Standardization Sample (Study 3)

Variable	*M*	*SD*	Range	1	2	3	4	5
1. ES	0.10	1.00	−2.8–2.8	—				
2. E	0.09	1.00	−2.8–2.8	.48**	—			
3. O	0.05	1.00	−2.6–2.5	.32**	.34**	—		
4. A	0.08	1.00	−2.8–2.2	.60**	.30**	.31**	—	
5. C	0.08	1.00	−2.8–2.6	.48**	.23**	.21**	.47**	—

Note. $N = 518$. ES = Emotional Stability; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness.
** $p < .01$, two-tailed.

Table 5
Descriptive Statistics and Intercorrelations Among Performance Ratings for Study 3

Variable	*N*	*M*	*SD*	Range	1	2	3	4	5	6
1. SUP98	47	12.60	1.17	10.21–14.65	—					
2. SUP99	52	12.60	1.34	8.25–14.55	.74**	—				
3. SUP00	78	12.79	1.13	10.30–14.90	.73**	.67**	—			
4. SELF98	43	12.90	1.31	9.72–15.70	.70**	.43**	.56**	—		
5. SELF99	47	12.51	1.41	9.10–15.00	.63**	.63**	.57**	.75**	—	
6. SELF00	74	12.42	1.29	7.80–15.05	.54**	.54**	.66**	.63**	.79**	—

Note. SUP98, SUP99, and SUP00 = supervisor-rated performance for the Years 1998, 1999, and 2000, respectively; SELF98, SELF99, and SELF00 = self-rated performance for the Years 1998, 1999, and 2000, respectively.
** $p < .01$, two-tailed.

D-PFCA Predicts Job Performance

There was a negative correlation between D-PFCA and age of $r = -.32$ ($n = 49$, $p = .02$, two-tailed). Descriptive statistics for D-PFCA and the relationship between D-PFCA and job performance are provided in Table 7. Three subsets of participants were identified by experience level (Dunnette, 1966; H. R. Rothstein, 1990). The Level 1 group ($n = 80$) consisted of all participants with 1 or more years of experience. This group contained all participants. The Level 2 group ($n = 53$), a subset of the Level 1 group, contained all participants with 2 or more years of experience. The Level 3 group ($n = 47$), a subset of the Level 2 group, contained all participants with 3 or more years of experience. D-PFCA was significantly correlated with supervisor-rated job performance in each of these overlapping groups, with $r = .42$, $r = .53$, and $r = .57$ for Levels 1, 2, and 3, respectively. Looking at this relationship within nonoverlapping subsamples, the correlation between D-PFCA and supervisor-rated performance was significantly higher ($Z = 2.11$, $p = .035$, two-tailed) for those with 3 or more years of experience ($r = .57$, $n = 47$, $p < .001$, one-tailed) than for those with less than 2 years of experience ($r = .12$, $n =$

Table 6
Descriptive Statistics and Intercorrelations for Personality and Job Performance for Studies 3 and 4

Variable	*M*	*SD*	Range	1	2	3	4	5	6	7	8
Study 3 (*N* = 80) Personality											
1. ES	0.43	0.93	−2.0–2.2	—							
2. E	0.16	1.00	−1.9–2.8	.52**	—						
3. O	−0.05	0.98	−2.5–1.8	.64**	.62**	—					
4. A	0.30	1.00	−2.2–2.2	.73**	.48**	.49**	—				
5. C	0.53	0.75	−1.0–2.1	.63**	.45**	.55**	.71**	—			
Job performance											
6. SUPPERF	12.64	1.08	9.32–14.58	.01	−.08	.03	.07	.08	—		
7. SELFPERF[a]	12.46	1.22	9.08–14.93	.20	.28*	.24*	.19	.23*	.64**	—	
8. PERF	12.57	1.05	9.80–14.50	.12	.10	.14	.14	.18	.91**	.91**	—
Study 4 (*N* = 96) Personality											
1. ES	0.56	0.97	−1.9–2.8	—							
2. E	0.46	1.01	−2.8–2.8	.41**	—						
3. O	0.12	0.96	−2.5–2.5	.65**	.59**	—					
4. A	0.50	0.97	−2.8–2.2	.59**	.13	.39**	—				
5. C	0.55	0.85	−1.2–2.6	.67**	.36**	.54**	.53**	—			
Job performance											
6. SUPPERF[b]	14.98	1.49	10.40–18.44	.06	.14	.13	.09	.23*	—		
7. SELFERF	—	—	—	—	—	—	—	—	—	—	
8. PERF	—	—	—	—	—	—	—	—	—	—	—

Note. $N = 80$. ES = Emotional Stability; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness; SUPPERF = supervisor-rated performance; SELFPERF = self-rated performance; PERF = composite of supervisor- and self-rated performance.
[a] $N = 77$ for this variable because of missing data. [b] $N = 94$ for this variable because of missing data.
* $p < .05$, two-tailed. ** $p < .01$, two-tailed.

Table 7
Descriptive Statistics and Intercorrelations for Job Performance and Dorsolateral Prefrontal Cognitive Ability by Experience for Study 3

Variable	*M*	*SD*	Range	1	2	3	4
Level 1: Workers with 1 or more years of experience, $N = 80$							
1. SUPPERF	12.64	1.08	9.33–14.58	—			
2. SELFPERF[a]	12.46	1.22	9.08–14.93	.64**	—		
3. PERF	12.57	1.05	9.80–14.50	.90**	.91**	—	
4. D-PFCA	−0.37	0.53	−1.81–1.07	.42**	.36**	.41**	—
Level 2: Workers with 2 or more years of experience, $N = 53$							
1. SUPPERF	12.71	1.13	9.33–14.58	—			
2. SELFPERF	12.56	1.30	9.08–14.93	.65**	—		
3. PERF	12.63	1.11	9.80–14.37	.90**	.91**	—	
4. D-PFCA	−0.35	0.55	−1.81–1.07	.53**	.50**	.56**	—
Level 3: Workers with 3 or more years of experience, $N = 47$							
1. SUPPERF	12.72	1.18	9.33–14.58	—			
2. SELFPERF	12.74	1.26	9.08–14.93	.73**	—		
3. PERF	12.72	1.14	9.80–14.37	.93**	.93**	—	
4. D-PFCA	−0.35	0.58	−1.81–1.07	.57**	.53**	.59**	—

Note. SUPPERF = supervisor-rated performance; SELFPERF = self-rated performance; PERF = composite of supervisor- and self-rated performance; D-PFCA = dorsolateral prefrontal cognitive ability.
[a] $N = 77$ for this variable because of missing data.
** $p < .01$, one-tailed.

27, $p = .28$). Regression analysis, predicting D-PFCA using self-ratings and supervisor performance ratings ($R = .45$, adjusted $R^2 = .18$), $F(2, 74) = 9.6$, $p < .001$, indicated that the independent relationship between supervisor ratings and D-PFCA ($sr = .28$) was significant, $t(74) = 2.69$, $p = .009$, whereas the relationship between self-ratings and D-PFCA ($sr = .10$) was not.

Discussion

D-PFCA Prediction of Job Performance

On the basis of previous meta-analyses (Hunter & Hunter, 1984), Schmidt and Hunter (1998) reported that general mental ability (GMA), or intelligence, is an excellent predictor of job performance, with the corrected predictive validity of GMA estimated at .51 for medium-complexity jobs (62% of U.S. jobs) and .58 for professional–managerial jobs. In the present study, the (uncorrected) correlation between D-PFCA and supervisor-rated job performance was $r = .42$ for the whole sample and $r = .57$ when only those with at least 3 years of experience were included. Similar results were found for self-rated job performance. For supervisor performance ratings, correction for attenuation due to the unreliability of the supervisor-rated performance composite ($\alpha = .88$) and the unreliability of the D-PFCA scores ($\alpha = .72$) revealed an estimated construct-level validity (correlation between true D-PFCA scores and true performance scores) of $r = .52$ for the whole sample and $r = .72$ for the most restrictive experience-level group (Level 3). The corrected values of $r = .52$–$.72$ compare well with Hunter and Schmidt's (1996) estimates, suggesting that D-PFCA predicts job performance at least as well as GMA.

D-PFCA Prediction of Job Performance and Its Relationship to Experience

Although it is often presumed that the relative importance of cognitive ability decreases as experience level increases, this presumption does not appear to be correct (Hunter & Schmidt, 1996). In fact, the empirical evidence suggests the reverse: The relationship between cognitive ability and performance increases with experience. McDaniel (cited in Hunter & Schmidt, 1996), for example, found that the validity of cognitive ability increased from .35 for 0 to 6 years, to .44 for 6 to 12 years, to .59 for more than 12 years. McDaniel's results for general cognitive ability are consistent with the results found in this study, as D-PFCA became significantly more important in predicting job performance as level of experience increased. This could mean that individuals become assessed more accurately as time goes on (Dunnette, 1966; H. R. Rothstein, 1990) or that the effect of cognitive ability on performance actually increases over time (Hunter & Schmidt, 1996), or both.

D-PFCA and Aging

This study also found a significant correlation between age and D-PFCA of $r = -.32$. This finding is in keeping with a large body of research suggesting the existence of a linear decline in cognitive function over the life span (Kramer & Willis, 2002). Age data were available for a subset of the sample ($n = 49$). The majority of those employees had at least 3 years of experience ($n = 44$), whereas the remainder had at least 2. Consequently, the age analysis largely consisted of Level 3 employees. Although there was a relationship between D-PFCA and age, the correlation between age and supervisor-rated performance was not significant, and controlling for age did not substantially affect the relationship between D-PFCA and supervisor-rated performance, suggesting that the relationship between D-PFCA and supervisor-rated performance may hold independent of age, at least for this subgroup.

Personality and Performance

Construct-level validity for Conscientiousness (i.e., correlation between personality trait and job performance, corrected for sampling error, range restriction, and attenuation due to the unreliabilities of both the personality trait and job performance measures) has been estimated at .22 (Barrick & Mount, 1991), .25 (Salgado, 1997), and .22 (Hurtz & Donovan, 2000). On the other hand, the mean observed correlation between Conscientiousness and performance (without any corrections) was .13 (Barrick & Mount, 1991), .10 (Salgado, 1997), and .14 (Hurtz & Donovan, 2000). The uncorrected value of $r = .08$ for Conscientiousness and supervisor-rated performance obtained in the present study is consistent with the other uncorrected values, although nonsignificant. Although the uncorrected value of $r = .23$ for Conscientiousness and self-rated performance is high, this result appears of dubious practical utility, given the lack of relationship with supervisor-rated performance. It might be assumed that in performance situations, Emotional Stability, Extraversion, Openness, Agreeableness, and Conscientiousness would each be more explicitly valued than their polar opposites. Consistent with this assumption, self-rated performance was positively and relatively strongly related to each personality trait, whereas supervisor-rated performance was inconsistently (with regard to direction) and weakly related to the personality traits. In terms of employment decisions, these data suggest that self-report personality measures may tell employers a good deal about how a prospective employee will rate, or overrate, his or her own performance, at least under some circumstances, but less about his or her performance as seen from the perspective of his or her supervisor.

STUDY 4

For Study 4, we tested a group of factory floor workers and their immediate floor supervisors using the FDTI and the D-PFCA battery described above. For these workers, only immediate supervisor performance ratings were available. We hypothesized that the predictive utility of D-PFCA would be attenuated in this situation, in which performance was probably more amenable to rote learning, but that Conscientiousness and Emotional Stability might emerge as useful predictors.

Method

Participants

Ninety-six factory floor workers participated in the study. Forty-six were female. The sample included assemblers, laborers, fabricators, machine operators, crew leaders, supervisors, and employees holding other factory floor positions. The average age of the participants was 38.3 years ($n = 95$, $SD = 9.7$ years, range: 20–58 years).

Materials

As in Study 3, employees were assessed on two occasions per year (Occasions a and b). On each occasion, employees were rated on five categories: productivity and quality, safety and housekeeping, human relations, responsibility and personal development, and dependability and responsiveness. The maximum score for each category was 20 points. Consequently, each performance report contained 10 scores: five from Occasion a and five from Occasion b. Performance evaluations were available for four years: 1998, 1999, 2000, and 2001. Year 2000 reports were available for 89 employees and were used to assess the reliability of the annual assessment form (coefficient $\alpha = .92$).

Procedure

Participants completed the FDTI (Study 3) and the D-PFCA battery (Study 1). Performance data, date of birth, date hired, and years of education were derived from the corporation's records.

Results

Performance Ratings and Work Experience

Descriptive statistics and intercorrelations among the annual performance ratings are presented in Table 8. The average intercorrelation among the annual performance ratings was $r_{\text{ave}} = .76$. As in Study 3, the annual performance ratings were averaged across the available years to produce a composite performance variable, SUPPERF. On the basis of the intercorrelations across the annual performance ratings, the reliability (coefficient α) of this composite variable was .91.

Table 8 also presents the mean and standard deviation for work experience (EXPER), the number of years the employees had been working with the corporation. There was a significant positive correlation between work experience and job performance across all four performance assessment years (see Table 8).

D-PFCA, Age, Experience, Education, and Job Performance

Descriptive statistics and intercorrelations for D-PFCA, age, years of education, experience, and job performance are given in Table 9. As in Study 3, there was a significant negative correlation between D-PFCA and age and a near-significant positive correlation between D-PFCA and years of education ($r = .18$, $n = 93$, $p = .09$, two-tailed). The partial correlation between D-PFCA and years of education, controlling for age, was $pr = .24$ ($df = 90$, $p = .02$, two-tailed).

The correlation between D-PFCA and job performance was not significant. However, this sample was quite heterogeneous in terms of years of experience, which was related to job performance, and age, which was related to D-PFCA. The partial correlation between D-PFCA and job performance, controlling for experience and age, was $pr = .18$ ($df = 89$, $p = .04$, one-tailed) and was $pr = 0.21$ ($df = 86$, $p = .02$, one-tailed) when years of education were added to the list of control variables.

Personality and Job Performance

Descriptive statistics and intercorrelations among personality variables and job performance are presented in Table 6. As in Study 3, the intercorrelations among the personality variables were quite high; however, only Conscientiousness had a statistically significant correlation with job performance.

Table 8
Descriptive Statistics and Intercorrelations for Performance Ratings and Job Experience for Study 4

Variable	*N*	*M*	*SD*	Range	1	2	3	4	5	6
1. PERF98	64	14.93	1.49	11.80–18.40	—					
2. PERF99	79	14.99	1.64	10.40–19.20	.82**	—				
3. PERF00	93	15.12	1.58	11.80–19.07	.67**	.80**	—			
4. PERF01	71	15.24	1.58	10.40–19.20	.64**	.71**	.89**	—		
5. SUPPERF	94	14.98	1.49	10.40–18.44	.88**	.93**	.94**	.92**	—	
6. EXPER	96	7.61	6.78	0–27	.25*	.36**	.23*	.23*	.30**	—
					Sample size for correlations					
1. PERF98					—					
2. PERF99					64	—				
3. PERF00					64	79	—			
4. PERF01					47	60	70	—		
5. SUPPERF					64	79	93	71	—	
6. EXPER					64	79	93	71	94	—

Note. PERF98, PERF99, PERF00, and PERF01 = supervisor-rated job performance for 1998, 1999, 2000, 2001, respectively; SUPPERF = average of annual performance ratings for Years 1998 to 2001; EXPER = number of years of job experience.
* $p < .05$, two-tailed. ** $p < .01$, two-tailed.

Full Regression Model

When performance was regressed on experience, D-PFCA, and Conscientiousness, controlling for age and years of education, the *R* for regression was .42, which was significant, $F(5, 85) = 3.66$, $p < .005$. The adjusted R^2 was .13. The standardized regression coefficients for experience, D-PFCA, and Conscientiousness were $\beta = .32$, .19, and .18, respectively ($sr = .32$, .17, and .17, respectively) and were significant (*p*s = .01, .04, and .04, all one-tailed, respectively). The regression coefficients for age and years of education ($\beta = .09$ and $-.11$, respectively) were not significant.

Discussion

A nonsignificant zero-order correlation between D-PFCA and job performance was found in the sample of skilled and semiskilled workers. This result appears attributable to a combination of factors: contamination by age and experience, attenuation for unreliability, and, perhaps, the fact that simpler jobs are less dependent on cognitive ability. As in Study 3, a significant negative correlation was found between D-PFCA and age, as well as a near-significant correlation between D-PFCA and years of education. In addition, the skilled and semiskilled workers in this study varied substantially in years of experience, which was related to job performance. When age, years of education, and experience were controlled for, the partial correlation between D-PFCA and performance was a significant $pr = .21$.

The correlation between D-PFCA and performance found in this study was significantly lower than the correlation found in Study 3 ($Z = 2.11$, $p = .03$, two-tailed). The difference may be explainable largely in terms of job complexity. Study 3 focused on predicting performance for medium-complexity and professional–managerial jobs, whereas Study 4 focused on low-complexity jobs. Higher complexity jobs are associated with a higher range of performance output

Table 9
Descriptive Statistics and Intercorrelations for D-PFCA, Age, Experience, Education, and Job Performance for Study 4

Variable	*N*	*M*	*SD*	Range	1	2	3	4	5
1. D-PFCA	96	−0.57	0.53	−1.94–1.11	—				
2. Age (years)	95	38.25	9.73	20–58	−.23*	—			
3. YEARSEDU	93	12.57	1.32	10–17	.18	.22*	—		
4. EXPER	96	7.61	6.78	0–27	−.15	.11	−.07	—	
5. SUPPERF	94	14.98	1.49	10.40–18.44	.12	.06	−.07	.30**	—
					Sample size for correlations				
1. D-PFCA					—				
2. Age (years)					95	—			
3. YEARSEDU					93	93	—		
4. EXPER					96	95	93	—	
5. SUPPERF					94	93	91	94	—

Note. D-PFCA = dorsolateral prefrontal cognitive ability; YEARSEDU = years of education; EXPER = years of experience on the job; SUPPERF = supervisor-rated job performance averaged across Years 1998–2001.
* $p < .05$, two-tailed. ** $p < .01$, two-tailed.

than lower complexity jobs, and the predictive validity of cognitive tests for higher complexity jobs (.51–.58) tends to be higher than that for lower complexity jobs (.38; Hunter & Schmidt, 1996).

In recent meta-analytic studies, the construct-level (corrected) validity for Conscientiousness was .22 (Barrick & Mount, 1991), .23 (Salgado, 1997), and .17 (Hurtz & Donovan, 2000), whereas the mean observed correlations between Conscientiousness and job performance were .13 (Barrick & Mount, 1991), .09 (Salgado, 1997), and .10 (Hurtz & Donovan, 2000) for the specific occupational category of skilled or semiskilled labor. In Study 4, in which the sample consisted primarily of skilled and semiskilled workers, the measured correlation between Conscientiousness and supervisor-rated job performance was .23. Thus, this study underscores the importance of Conscientiousness for skilled and semiskilled job performance.

Overall, for the relatively low-complexity work completed by these skilled and semiskilled workers, experience appears to be an important determinant of performance level, with D-PFCA and Conscientiousness each independently and incrementally contributing to performance.

GENERAL DISCUSSION

D-PFCA and Predicting Performance

In combination, Studies 1 and 2 demonstrate the importance of D-PFCA and Conscientiousness in predicting academic performance. Together, D-PFCA and Conscientiousness appear to predict academic performance in very competitive environments as well as IQ and g and independent of both. These results suggest that a nontrivial slice of the variance in academic performance might be accounted for using these alternative measures. In addition, Studies 1 and 2 also help clarify the relationship between D-PFCA and intelligence as traditionally understood (in terms of the correlation between D-PFCA and IQ and SAT, but also with regard to the ability of D-PFCA to predict academic performance, the traditional criterion for intelligence testing). In the process, they demonstrate that intelligence can be thought of in part in terms of working memory, conditional associative learning, and word fluency—putative aspects of dorsolateral cognitive prefrontal functioning—as well as, or in addition to, more traditional psychometric concepts.

The most outstanding feature of Studies 3 and 4 was the successful generalization of the finding that D-PFCA predicts real-world performance from the clinical and academic to the industrial–organizational context. Among managers and administrators, D-PFCA and performance were related at uncorrected rs of ~.40–.60 and corrected rs of ~.50–.70. These are large effects (Rosenthal, 1990), with equally large potential economic implications. Schmidt and Hunter (1998) offered a formula for the calculation of productivity increase as a consequence of use of psychometric testing, using their previous work on output variability as the essential basis for the calculation (Hunter, Schmidt, & Judiesch, 1990). According to their formula, the addition of D-PFCA testing to hiring in a company using unstructured interviews (which have a corrected validity coefficient of $r = .38$) for employees making $75,000 per annum would result in a productivity increase of 33% of salary—$25,000 per year and $125,000 over the 5 years that the typical individual stays in a typical high-complexity position (Schmidt & Hunter, 1998; assuming a one out of 10 hiring rate, a high-complexity job, and an uncorrected $r = .57$ between multiyear ratings of managerial–administrative performance).

Conscientiousness and Performance

Conscientiousness has previously been shown to predict academic (Goff & Ackerman, 1992; E. K. Gray & Watson, 2002; M. G. Rothstein et al., 1994) and job performance (Barrick & Mount, 1991; Hurtz & Donovan, 2000; Salgado, 1997). Such analyses have revealed a mean predictive validity for Conscientiousness of $r = \sim.20$. Although Conscientiousness was not associated with performance in Study 3, in Study 4, Conscientiousness and supervisor-rated job performance were correlated at $r = .23$, and in Studies 1 and 2, Conscientiousness was related to academic performance over and above IQ and D-PFCA.

It is likely that Conscientiousness exerts its effect on academic performance indirectly. Theoretically, it is Openness that has been associated with intelligence (L. R. Goldberg, 1990), and Openness has been found to correlate positively with IQ in past research (John & Srivastava, 1999). This result was replicated in Studies 1 and 2. However, in Studies 1 and 2, it was Conscientiousness, not Openness, that was correlated with academic performance. There is evidence that the effects of Conscientiousness on job performance are mediated by goal setting (Barrick, Mount, & Strauss, 1993; Gellatly, 1996), autonomy (Barrick & Mount, 1993), and motivation (Barrick, Stewart, & Piotrowski, 2002). Given the lack of relationship between Conscientiousness and D-PFCA and intelligence, it is possible that Conscientiousness exerts its effect on performance indirectly through self-management. It is possible that Conscientiousness reflects a motivational tendency, or desire, to be organized, thorough, planful, efficient, responsible, reliable, dependable, and so on (trait-adjective list from John & Srivastava, 1999), whereas D-PFCA may reflect the ability to make effective plans, to initiate them and regulate them, to inhibit distracting activities and stimuli, and to monitor outcomes in the pursuit of some posited goal state.

In each study, personality scores deviated from their theoretical orthogonality. This was particularly pronounced in Studies 3 and 4, in which the FDTI was used to predict job performance. Although the FDTI was characterized by relatively high scale intercorrelations during standardization and that may point to some degree of methodological flaw in its construction, it also appears likely that in employment contexts, participants may be both motivated and able to present themselves as conscientious, emotionally stable, agreeable, extraverted, and open-minded–intelligent—that is, as personality types that might seem ideal to employers. This suggestion appears consistent with the statistically significant correlation of personality with self-rated performance found in Study 3 ($r = .23$), as opposed to the nonsignificant association found between personality and supervisor-rated performance ($r = .08$) found in the same sample. In Studies 1 and 2, there was a strong relationship between Conscientiousness and academic performance, in which presentational pressures were essentially absent.

Overall, these results add credence to the notion that personality might be usefully assessed in academic and industrial–organizational settings. The possibility that self-presentation bias reduces its validity should not be dismissed. Although recent articles have suggested that correcting for presentational bias using putative measures of response validity does not appear useful (Hough, Eaton, Dunnette, Kame, & McCloy, 1990; Ones, Viswesvaran, & Reiss, 1996), it still may be necessary to develop Big Five tests that are not susceptible to self-presentation effects.

D-PFCA and the Hierarchical Model of Psychometric Intelligence

Duncan (Duncan, Burgess, & Emslie, 1995) has already attempted to establish the relationship between dorsolateral prefrontal processing and Spearman's *g*, using methods different from ours. First, he demonstrated that individuals with frontal lobe damage are susceptible to goal neglect (Duncan et al., 1996), which is relatively more likely to occur under conditions of novelty or ambiguity, and to attendant task failure. He also demonstrated that individuals with low scores on Cattell's Culture-Fair Test (an intelligence test with a *g* factor loading of around .80; Jensen, 1980, p. 650) are also susceptible to this failing. Finally, using PET, Duncan et al. (2000) have also shown that participants are characterized by increased activation in dorsolateral prefrontal cortex when solving highly *g*-loaded problems.

The paradox of sustained IQ scores after severe frontal lobe damage (Stuss & Benson, 1986) can, in Duncan's opinion, be resolved by drawing on Cattell's (1987) distinction between fluid and crystallized intelligence (Duncan et al., 1995). According to this view, the WAIS primarily measures crystallized intelligence, whereas Cattell's Culture-Fair Test primarily measures fluid intelligence. In a sample of three patients with high IQ scores after frontal lobe damage, Duncan and his colleagues demonstrated relatively poor performance on Cattell's Culture-Fair Test, permitting Duncan et al. (1995) to argue that fluid intelligence is diminished in the frontal patients, whereas crystallized intelligence (WAIS IQ) is preserved. Taken together, these findings support the argument that dorsolateral prefrontal cortex is the neural basis for Spearman's *g*, or general intelligence.

However, there are a number of conceptual problems with this position. Psychometric *g* is as conceptually delicate as it is empirically robust, and although Duncan has advanced the understanding of intelligence, he nonetheless appears to have made a conceptual error in equating Cattell's Culture-Fair Test scores with *g*. Psychometric *g* is a statistical regularity, reflecting the positive intercorrelations among all tests of mental ability. Although Cattell's Culture-Fair Test and RPM are highly *g*-loaded tests, neither is required to locate *g*. Psychometric *g* can be located quite accurately using the WAIS (Jensen, 1998)—performance on which, as Duncan et al. (1995) argued, may not be critically dependent on the dorsolateral prefrontal cortex. Jensen (1998, p. 91) estimated that the *g* loading of a standard IQ test (e.g., the WAIS) is around .80—a figure identical to that of Cattell's test.

Consider for a moment the likely performance of a large sample of prefrontal patients such as those used by Duncan et al. (1995)—that is, patients who are impaired on Cattell's Culture-Fair Test but not on the WAIS. Suppose that these patients completed a number of typical IQ tests, such as the WAIS, the Stanford-Binet, and the Armed Services Vocational Aptitude Battery. Given (a) that performance on traditional intelligence tests is preserved in the case of prefrontal damage and (b) that the positive manifold appears universal, it seems certain that factor analysis of the subtest scores of all these brain-damaged patients would still allow extraction of a first, *g*-like factor. It might also be argued (c) that the patients' premorbid Cattell's Culture-Fair Test factor scores would also be highly correlated with their postmorbid factor scores (that is, that the rank-ordering of the patients might be roughly preserved, assuming rough equivalence of damage). If these three suppositions are true, then the *g* factor can still easily be located after partial destruction of the frontal lobes, and the neural basis for *g* has not in fact been destroyed. It is therefore no more correct to equate Cattell's Culture-Fair Test scores with *g* than to equate WAIS scores with *g*. It is also worth remembering that performance on various intelligence tests correlates with inspection time, choice reaction time, brain size, EEG characteristics, and possibly nerve conduction velocity and metabolic activity (see Deary, 2000, for review)—characteristics that are certainly not specifically dependent on dorsolateral PFC function.

Duncan et al. (2000) did demonstrate that there was more intense neural activity in the dorsolateral prefrontal cortex when participants were solving high-*g* rather than low-*g* problems. In that study, however, Duncan et al. used matrix problems and letter-based problems, all of which required participants to examine four sets of patterns and choose the pattern that did not fit with the other three. All items, high or low *g*, had this form. The primary difference between the high- and low-*g* items was therefore the complexity of the problem, or the number of rules and variables the participant was required to process simultaneously. This implies that the primary difference between Duncan's putative high- and low-*g* items was in fact the load placed on working memory (Baddeley, 1986). Rather than demonstrating that the dorsolateral prefrontal cortex is the neural basis of Spearman's *g*, Duncan et al. have likely replicated the well-established finding that the dorsolateral prefrontal cortex is critically involved in working memory. Although it is clear that any account of intelligence that does not incorporate the concept of working memory is likely to be incomplete (Ackerman et al., 2005; Kane & Engle, 2002; Kyllonen & Christal, 1990), the broad range of correlates of *g* suggests that it is unlikely that working memory is identical to *g*. It should also be recalled that higher *g* scores are associated with higher gray matter volume overall, not just with higher gray matter volume in the frontal cortex (Thompson et al., 2001; Thompson, Cannon, & Toga, 2002), and that the neural correlates of *g* probably extend beyond the prefrontal cortex (J. R. Gray et al., 2003; MacLullich et al., 2002).

Given all this, how might the relationship between D-PFCA, intelligence, and academic performance be conceptualized? It appears to us that the relationship is partly a consequence of the immediate impact of D-PFCA, particularly with regard to working memory, and partly a consequence of its delayed, developmental impact. D-PFCA may reflect individual differences in a student's day-to-day and month-to-month ability to plan and organize behavior in the pursuit of intrinsically generated goals, allowing for effective orientation in a novel physical and social environment, and successful direction of behavior toward the completion of (academic) goals (Duncan, 1995; Luria, 1980; E. K. Miller, 2000; Stuss & Benson, 1986). The neuropsychological literature attests to the importance of the frontal lobes in dealing with novelty (E. Goldberg, 2001), regulating social behavior (Damasio, 1994), and initiating and monitoring goal-directed activity (Luria, 1980). As Jensen (1980, p. 331) pointed out, students in college—unlike elementary and high school students—are essentially self-directed and self-organized and do not experience constant external discipline imposed by a parent or a teacher. College students are therefore required to plan, organize, regulate, and evaluate their own behavior while striving to attain and maintain high levels of academic performance.

Additionally, consider something more subtle and developmental. Individuals with higher D-PFCA may be more capable of manipulating abstractions, both perceptual and verbal, and then organizing increasingly more automated and crystallized forms of intelligence over the course of their developmental history. The result would be a crystallized intelligence whose magnitude is correlated with the power of the original programmer (D-PFCA) but that remains psychometrically distinguishable (Cattell, 1987). In other words, dorsolateral prefrontal cortex, highly involved in the processing of novel information (Fletcher et al., 2001; Turner et al., 2004), may program cognitive abilities to a level of automation that is no longer physiologically dependent on the prefrontal cortex (Sakai et al., 1998; Shariff & Peterson, 2005) but that remains correlated with it. Such abilities might include vocabulary breadth and letter recognition speed, for example—highly practiced skills that, once mastered, are relegated to specialized brain areas.

Figure 1 presents our attempt to provide a provisional model for the relationship between physiological–neuropsychological and standard hierarchical models of psychometric intelligence. It is predicated on the idea that D-PFCA broadens people's conception of and ability to measure something roughly equivalent, but not identical, to fluid intelligence. Each of the levels of overlapping circles represents a perspective on intelligence informed by different data, from the more biologically concrete to the more statistically abstract. At the most basic level, there exists an array of interrelated physical phenomena, partially represented at the bottom level of Figure 1 as brain volume/organization, prefrontal volume/organization, and neural transmission speed (this is intended as a schematic rather than a comprehensive portrayal of brain function and intelligence). Clearly, total brain volume/organization and prefrontal volume/organization are both highly correlated and somewhat separable (MacLullich et al., 2002), allowing measurements of each phenomenon to independently pick up some of the variance in function, in addition to the substantive variance they necessarily share. Brain volume/organization also appears importantly associated with processing speed (via axonal diameter; Harrison, Hof, & Wang, 2002). The logical net consequence of the interrelationship between these physiological contributors to cognitive function is overlap in terms of cognitive ability: Larger brains have larger prefrontal cortices; larger brains with larger prefrontal cortices have thicker axons; brains with thicker axons are faster; larger brains with thicker, faster axons have an advantage in terms of cognitive function.

At the second level from the bottom of Figure 1 is a representation of the potential nature of the profound functional relationship between prefrontal cognitive abilities and the other primarily cognitive abilities of the brain. In light of the role of the prefrontal cortex in the construction of novel habits, skills, and concepts, it is reasonable to view it as the programmer of other brain areas. So, not only is there inseparable physiological overlap between the prefrontal cortex and other parts of the brain (in terms of size and speed) but also there is inseparable functional overlap (except in special, pathological cases and circumstances): Specific cognitive abilities, less prefrontally dependent in their mature form, are still what they are in no small part because of the novelty analysis and general programming capacity of the prefrontal cortex. What this means is (a) that more specific and less prefrontally dependent cognitive abilities will inevitably be contaminated with prefrontal ability because of the manner in which they were initially programmed and (b) that measures of nonprefrontally dependent

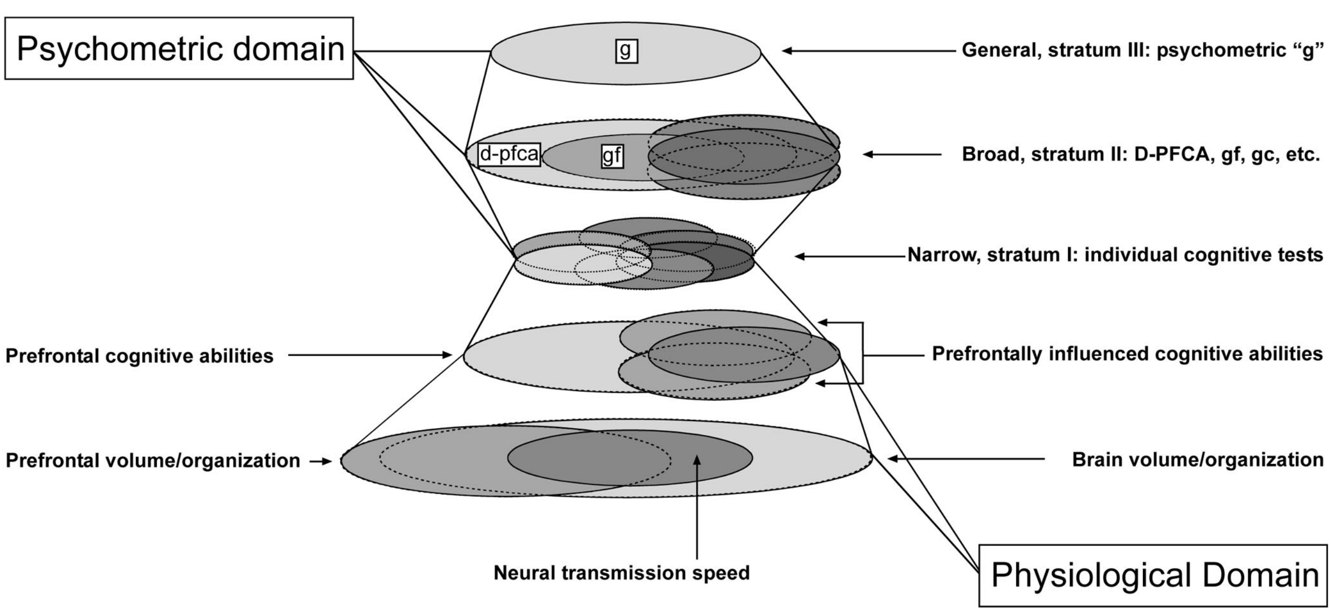

Figure 1. Intelligence in its putative physiological and psychometric forms and the relationship between those forms. D-PFCA = dorsolateral prefrontal cognitive ability; g = Spearman's g; gf = fluid intelligence; gc = crystallized intelligence.

intelligence (crystallized IQ, perceptual function) will inevitably reflect prefrontal function—even after prefrontal damage sustained in adulthood, if they are measured in adulthood, after a long developmental history.

The third level from the bottom in Figure 1 is the first of those in the psychometric and statistical domain. Imagine that the set of all possible cognitive functions is randomly sampled, with no a priori consideration given to weighting that sampling to accurately reflect underlying physiological architecture (Carroll, 1993). All such randomly selected measures are nonetheless going to be highly contaminated with prefrontal function or fluid intelligence because of the physiological and functional overlap between that brain area and all others, as previously described. This statistical contamination, inevitable because of the underlying physiological and functional overlap, finds its representation in the fourth level from the bottom, in the factor representing fluid intelligence, and in the fact of the high levels of correlation between all the so-called stratum II factors. Finally, at the topmost level, *g* emerges, very tightly associated, statistically, with fluid intelligence because of all the overlap of physiology, function, and measurement between prefrontal cognitive function and general brain function at the lower levels. Moreover, *g* emerges, reliably, even if there are no specific fluid intelligence measures at the narrow, Stratum I measurement level because all the specific subdomains of intelligence are inextricably contaminated with fluid intelligence or prefrontal cognitive ability, and a broad sampling of such tests will inevitably reflect that. We would therefore argue, in keeping with this model, that the D-PFCA battery used in our studies potentially picked up variance in academic performance independent of IQ and *g* because it more accurately sampled the D-PFCA functional domain at a psychometric level than may typically be the case with standard IQ or *g* measures.

References

Ackerman, P. L., Beier, M. E., & Boyle, M. D. (2002). Individual differences in working memory within a nomological network of cognitive and perceptual speed abilities. *Journal of Experimental Psychology: General, 131,* 567–589.

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin, 131,* 30–60.

Anastasi, A., & Urbina, S. (1997). *Psychological testing* (7th ed.). Upper Saddle River, NJ: Prentice Hall.

Anderson, B. (2003). Brain imaging and *g*. In H. Nyborg (Ed.), *The scientific study of general intelligence: Tribute to Arthur R. Jensen* (pp. 29–39). Boston: Elsevier.

Baddeley, A. D. (1986). *Working memory.* New York: Oxford University Press.

Barrick, M. R., & Mount, M. K. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology, 44,* 1–26.

Barrick, M. R., & Mount, M. K. (1993). Autonomy as a moderator of the relationships between the Big Five personality dimensions and job performance. *Journal of Applied Psychology, 78,* 111–118.

Barrick, M. R., Mount, M. K., & Strauss, J. P. (1993). Conscientiousness and performance of sales representatives: Test of the mediating effects of goal setting. *Journal of Applied Psychology, 78,* 715–722.

Barrick, M. R., Stewart, G. L., & Piotrowski, M. (2002). Personality and job performance: Test of the mediating effects of motivation among sales representatives. *Journal of Applied Psychology, 87,* 43–51.

Binet, A., & Simon, T. (1905). Méthodes nouvelles pour le diagnostic du niveau intellectual des anormaux [New methods for the diagnosis of the intellectual level of subnormals]. *L'Année Psychologique, 11,* 191–244.

Blair, C. (2006). How similar are fluid cognition and general intelligence? A developmental neuroscience perspective on fluid cognition as an aspect of human cognitive ability. *Behavioral and Brain Sciences, 29,* 109–160.

Boivin, M. J., Giordani, B., Berent, S., Amato, D. A., Lehtinen, S., Koeppe, R. A., et al. (1992). Verbal fluency and positron emission tomographic mapping of regional cerebral glucose metabolism. *Cortex, 28,* 231–239.

Brand, C. R. (1996). *The g factor.* Chichester, England: Wiley.

Brody, N. (1992). *Intelligence* (2nd ed.). San Diego, CA: Academic Press.

Brooker, B. H., & Cyr, J. J. (1986). Tables for clinicians to use to convert WAIS–R short forms. *Journal of Clinical Psychology, 42,* 982–986.

Carey, D. P. (2005). Executive function or *g*? Hmmmmm. *Cortex, 41,* 220–221.

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

Carver, C. S., & Scheier, M. F. (1998). *On the self-regulation of behavior.* Cambridge, England: Cambridge University Press.

Cattell, R. B. (1987). *Intelligence: Its structure, growth, and action.* Amsterdam: Elsevier Science.

Conway, A. R. A., Cowan, N., Bunting, M. F., Therriault, D. J., & Minkoff, S. R. B. (2002). A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence, 30,* 163–184.

Conway, A. R. A., Kane, M. J., Bunting, M. F., Hambrick, D. Z., Wilhelm, O., & Engle, R. W. (2005). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin & Review, 12,* 769–786.

Conway, A. R. A., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in Cognitive Sciences, 7,* 547–552.

Costa, P. T., & McCrae, R. R. (1992). *Revised NEO Personality Inventory (NEO PR-I) and NEO Five-Factor Inventory (NEO-FFI): Professional manual.* Odessa, FL: Psychological Assessment Resources.

Costa, P. T., & McCrae, R. R. (1997). Longitudinal stability of adult personality. In R. Hogan, J. A. Johnson, & S. Briggs (Eds.), *Handbook of personality psychology* (pp. 269–290). San Diego, CA: Academic Press.

Cyr, J. J., & Brooker, B. H. (1984). Use of appropriate formulas for selecting WAIS–R short forms. *Journal of Consulting and Clinical Psychology, 52,* 903–905.

Damasio, A. R. (1994). *Descartes' error: Emotion, reason, and the human brain.* New York: Putnam.

Damasio, A. R., & Anderson, S. W. (1993). The frontal lobes. In K. M. Heilman & E. Valenstein (Eds.), *Clinical neuropsychology* (3rd ed., pp. 409–460). New York: Oxford University Press.

Deary, I. J. (2000). *Looking down on human intelligence: From psychometrics to the brain.* Oxford, England: Oxford University Press.

Deary, I. J. (2001). Human intelligence differences: A recent history. *Trends in Cognitive Sciences, 5,* 127–130.

Deary, I. J. (2005). The principles of cognition and the abilities of man: A natural collaboration. *Cortex, 41,* 225–227.

DeYoung, C. G., Peterson, J. B., & Higgins, D. M. (2002). Higher-order factors of the Big Five predict conformity: Are there neuroses of health? *Personality and Individual Differences, 33,* 533–552.

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology, 41,* 417–440.

Duncan, J. (1995). Attention, intelligence, and the frontal lobes. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences* (pp. 721–733). Cambridge, MA: MIT Press.

Duncan, J. (2005). Frontal lobe function and general intelligence: Why it matters. *Cortex, 41,* 215–217.

Duncan, J., Burgess, P., & Emslie, H. (1995). Fluid intelligence after frontal lobe lesions. *Neuropsychologia, 33,* 261–268.

Duncan, J., Emslie, H., Williams, P., Johnson, R., & Freer, C. (1996).

Intelligence and the frontal lobe: The organization of goal-directed behavior. *Cognitive Psychology, 30,* 257–303.
Duncan, J., Seitz, R. J., Kolodny, J., Bor, D., Herzog, H., Ahmed, A., et al. (2000, July 21). A neural basis for general intelligence. *Science, 289,* 457–460.
Dunnette, M. D. (1966). *Personnel selection and placement.* Oxford, England: Wadsworth.
Eysenck, H. J. (1998). *Intelligence: A new look.* New Brunswick, NJ: Transaction Publishers.
Fletcher, P. C., Anderson, J. M., Shanks, D. R., Honey, R., Carpenter, T. A., Donovan, T., et al. (2001). Responses of human frontal cortex to surprising events are predicted by formal associative learning theory. *Nature Neuroscience, 4,* 1043–1048.
Frith, C. D., Friston, K. J., Liddle, P. F., & Frackowiak, R. S. (1991). A PET study of word finding. *Neuropsychologia, 29,* 1137–1148.
Fuster, J. M. (1997). *The prefrontal cortex: Anatomy, physiology, and neuropsychology of the frontal lobe* (3rd ed.). Philadelphia: Lippincott.
Fuster, J. M. (2005). The cortical substrate of general intelligence. *Cortex, 41,* 228–229.
Gardner, H. (1993). *Frames of mind: The theory of multiple intelligences* (2nd ed.). New York: Basic Books.
Gellatly, I. R. (1996). Conscientiousness and task performance: Test of cognitive process model. *Journal of Applied Psychology, 81,* 474–482.
Gignac, G., Vernon, P. A., & Wickett, J., C. (2003). Factors influencing the relationship between brain size and intelligence. In H. Nyborg (Ed.), *The scientific study of general intelligence: Tribute to Arthur R. Jensen* (pp. 93–106). Boston: Elsevier.
Goff, M., & Ackerman, P. L. (1992). Personality–intelligence relations: Assessment of typical intellectual engagement. *Journal of Educational Psychology, 84,* 537–552.
Goldberg, E. (2001). *The executive brain: Frontal lobes and the civilized mind.* Oxford, England: Oxford University Press.
Goldberg, L. R. (1990). An alternative "description of personality": The Big-Five factor structure. *Journal of Personality and Social Psychology, 59,* 1216–1229.
Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment, 4,* 26–42.
Gottfredson, L. S. (1997). Why *g* matters: The complexity of everyday life. *Intelligence, 24,* 79–132.
Gottfredson, L. S. (2003). Dissecting practical intelligence theory: Its claims and evidence. *Intelligence, 31,* 343–397.
Gould, S. J. (1996). *The mismeasure of man* (Rev. ed.). New York: Norton.
Gray, E. K., & Watson, D. (2002). General and specific traits of personality and their relation to sleep and academic performance. *Journal of Personality, 70,* 177–206.
Gray, J. A., & McNaughton, N. (2000). *The neuropsychology of anxiety: An enquiry into the functions of the septo-hippocampal system* (2nd ed.). Oxford, England: Oxford University Press.
Gray, J. R., Chabris, C. F., & Braver, T. S. (2003). Neural mechanisms of general fluid intelligence. *Nature Neuroscience, 6,* 316–322.
Gray, J. R., & Thompson, P. M. (2004). Neurobiology of intelligence: Science and ethics. *Nature Reviews Neuroscience, 5,* 471–482.
Haier, R. J. (2003). Positron emission tomography studies of intelligence: From psychometrics to neurobiology. In H. Nyborg (Ed.), *The scientific study of general intelligence: Tribute to Arthur R. Jensen* (pp. 41–51). Boston: Elsevier.
Haier, R. J., Jung, R. E., Yeo, R. A., Head, K., & Alkire, M. T. (2004). Structural brain variation and general intelligence. *NeuroImage, 23,* 425–433.
Harrison, K. H., Hof, P. R., & Wang, S. S. (2002). Scaling laws in the mammalian neocortex: Does form provide clues to function? *Journal of Neurocytology, 31,* 289–298.
Herrnstein, R. J., & Murray, C. A. (1994). *The bell curve: Intelligence and class structure in American life.* New York: Free Press.
Hogan, R., Hogan, J., & Roberts, B. W. (1996). Personality measurement and employment decisions: Questions and answers. *American Psychologist, 51,* 469–477.
Hough, L. M., Eaton, N. K., Dunnette, M. D., Kame, J. D., & McCloy, R. A. (1990). Criterion-related validities of personality constructs and the effect of response distortion on those validities. *Journal of Applied Psychology, 75,* 581–595.
Hunter, J. E., & Hunter, R. F. (1984). Validity and utility of alternative predictors of job performance. *Psychological Bulletin, 96,* 72–98.
Hunter, J. E., & Schmidt, F. L. (1996). Intelligence and job performance: Economic and social implications. *Psychology, Public Policy, and Law, 2,* 447–472.
Hunter, J. E., Schmidt, F. L., & Judiesch, M. K. (1990). Individual differences in output variability as a function of job complexity. *Journal of Applied Psychology, 75,* 28–42.
Hurtz, G. M., & Donovan, J. J. (2000). Personality and job performance: The Big Five revisited. *Journal of Applied Psychology, 85,* 869–879.
Jensen, A. R. (1980). *Bias in mental testing.* New York: Free Press.
Jensen, A. R. (1994). Psychometric *g* related to differences in head size. *Personality and Individual Differences, 17,* 597–606.
Jensen, A. R. (1998). *The g factor: The science of mental ability.* Westport, CT: Praeger/Greenwood.
John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (2nd ed., pp. 102–138). New York: Guilford Press.
Kane, M. J., & Engle, R. W. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review, 9,* 637–671.
Kane, M. J., Hambrick, D. Z., & Conway, A. R. A. (2005). Working memory capacity and fluid intelligence are strongly related constructs: Comment on Ackerman, Beier, and Boyle (2005). *Psychological Bulletin, 131,* 66–71.
Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The generality of working memory capacity: A latent-variable approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology: General, 133,* 189–217.
Kramer, A. F., & Willis, S. L. (2002). Enhancing the cognitive vitality of older adults. *Current Directions in Psychological Science, 11,* 173–177.
Kyllonen, P. C., & Christal, R. E. (1990). Reasoning ability is (little more than) working-memory capacity?! *Intelligence, 14,* 389–433.
Lau, M. A., Pihl, R. O., & Peterson, J. B. (1995). Provocation, acute alcohol intoxication, cognitive performance, and aggression. *Journal of Abnormal Psychology, 104,* 150–155.
Lee, A. G. M., Higgins, D. M., Peterson, J. B., & Pihl, R. O. (2001, June). *Validation of a short self-administered computerized Big-Five personality test: The Five-Dimensional Temperament Inventory.* Poster session presented at the annual meeting of the American Psychological Society, Toronto, Ontario, Canada.
Loehlin, J. C., McCrae, R. R., Costa, P. T., Jr., & John, O. P. (1998). Heritabilities of common and measure-specific components of the Big Five personality factors. *Journal of Research in Personality, 32,* 431–453.
Luria, A. R. (1980). *Higher cortical functions in man* (2nd ed.). New York: Basic Books.
MacLullich, A. M. J., Ferguson, K. J., Deary, I. J., Seckl, J. R., Starr, J. M., & Wardlaw, J. M. (2002). Intracranial capacity and brain volumes are associated with cognition in healthy elderly men. *Neurology, 59,* 169–174.
McCrae, R. R., & Costa, P. T. (1997). Personality trait structure as a human universal. *American Psychologist, 52,* 509–516.
McDaniel, M. A. (2005). Big-brained people are smarter: A meta-analysis of the relationship between in vivo brain volume and intelligence. *Intelligence, 33,* 337–346.

Miller, E. K. (2000). The prefrontal cortex and cognitive control. *Nature Reviews Neuroscience, 1,* 59–65.

Miller, G. A., Eugene, G., & Pribram, K. H. (1960). *Plans and the structure of behavior.* New York: Holt.

Milner, B., & Petrides, M. (1984). Behavioural effects of frontal-lobe lesions in man. *Trends in Neurosciences, 7,* 403–407.

Milner, B., Petrides, M., & Smith, M. L. (1985). Frontal lobes and the temporal organization of memory. *Human Neurobiology, 4,* 137–142.

Neisser, U., Boodoo, G., Bouchard, T. J., Jr., Boykin, A. W., Brody, N., Ceci, S. J., et al. (1996). Intelligence: Knowns and unknowns. *American Psychologist, 51,* 77–101.

Neubauer, A. C., & Fink, A. (2003). Fluid intelligence and neural efficiency: Effects of task complexity and sex. *Personality and Individual Differences, 35,* 811–827.

Neubauer, A. C., Grabner, R. H., Fink, A., & Neuper, C. (2005). Intelligence and neural efficiency: Further evidence of the influence of task content and sex on the brain–IQ relationship. *Cognitive Brain Research, 25,* 217–225.

Neubauer, A. C., Grabner, R. H., Freudenthaler, H. H., Beckmann, J. F., & Guthke, J. R. (2004). Intelligence and individual differences in becoming neurally efficient. *Acta Psychologica, 116,* 55–74.

Oberauer, K., Schulze, R., Wilhelm, O., & Süβ, H.-M. (2005). Working memory and intelligence—Their correlation and their relation: Comment on Ackerman, Beier, and Boyle (2005). *Psychological Bulletin, 131,* 61–65.

Ones, D. S., Viswesvaran, C., & Reiss, A. D. (1996). The role of social desirability in personality testing for personnel selection: The red herring. *Journal of Applied Psychology, 81,* 660–679.

Peterson, J. B. (1999). *Maps of meaning: The architecture of belief.* New York: Routledge.

Peterson, J. B., Finn, P. R., & Pihl, R. O. (1992). Cognitive dysfunction and the inherited predisposition to alcoholism. *Journal of Studies on Alcohol, 53,* 154–160.

Peterson, J. B., Pihl, R. O., Higgins, D. M., Séguin, J. R., & Tremblay, R. E. (2003). Neuropsychological performance, IQ, personality, and grades in a longitudinal grade-school male sample. *Individual Differences Research, 1,* 159–172.

Petrides, M. (1982). Motor conditional associative-learning after selective prefrontal lesions in the monkey. *Behavioural Brain Research, 5,* 407–413.

Petrides, M. (1985a). Deficits in non-spatial conditional associative learning after periarcuate lesions in the monkey. *Behavioural Brain Research, 16,* 95–101.

Petrides, M. (1985b). Deficits on conditional associative-learning tasks after frontal- and temporal-lobe lesions in man. *Neuropsychologia, 23,* 601–614.

Petrides, M. (1986). The effect of periarcuate lesions in the monkey on the performance of symmetrically and asymmetrically reinforced visual and auditory go, no-go tasks. *Journal of Neuroscience, 6,* 2054–2063.

Petrides, M. (1987). Conditional learning and the primate frontal cortex. In E. Perecman (Ed.), *The frontal lobes revisited* (pp. 91–108). New York: IRBN Press.

Petrides, M. (1989). Frontal lobes and memory. In F. Boller & J. Grafman (Eds.), *Handbook of neuropsychology* (Vol. 3, pp. 75–90). Amsterdam: Elsevier Science.

Petrides, M. (1990). Nonspatial conditional learning impaired in patients with unilateral frontal but not unilateral temporal lobe excisions. *Neuropsychologia, 28,* 137–149.

Petrides, M. (1995a). Functional organization of the human frontal cortex for mnemonic processing: Evidence from neuroimaging studies. In J. Grafman, K. J. Holyoak, & F. Boller (Eds.), *Annals of the New York Academy of Sciences: Vol. 769. Structure and functions of the human prefrontal cortex* (pp. 85–96). New York: New York Academy of Sciences.

Petrides, M. (1995b). Impairments on nonspatial self-ordered and externally ordered working memory tasks after lesions of the mid-dorsal part of the lateral frontal cortex in the monkey. *Journal of Neuroscience, 15,* 359–375.

Petrides, M. (1998). Specialized systems for the processing of mnemonic information within the primate frontal cortex. In A. C. Roberts & T. W. Robbins (Eds.), *The prefrontal cortex: Executive and cognitive functions* (pp. 103–116). New York: Oxford University Press.

Petrides, M. (2000). The role of the mid-dorsolateral prefrontal cortex in working memory. *Experimental Brain Research, 133,* 44–54.

Petrides, M., Alivisatos, B., Evans, A. C., & Meyer, E. (1993). Dissociation of human mid-dorsolateral from posterior dorsolateral frontal cortex in memory processing. *Proceedings of the National Academy of Sciences, USA, 90,* 873–877.

Petrides, M., Alivisatos, B., Meyer, E., & Evans, A. C. (1993). Functional activation of the human frontal cortex during the performance of verbal working memory tasks. *Proceedings of the National Academy of Sciences, USA, 90,* 878–882.

Petrides, M., & Milner, B. (1982). Deficits on subject-ordered tasks after frontal- and temporal-lobe lesions in man. *Neuropsychologia, 20,* 249–262.

Plomin, R. (2001). The genetics of *g* in human and mouse. *Nature Reviews Neuroscience, 2,* 136–141.

Prabhakaran, V., Rypma, B., & Gabrieli, J. D. E. (2001). Neural substrates of mathematical reasoning: A functional magnetic resonance imaging study of neocortical activation during performance of the Necessary Arithmetic Operations Test. *Neuropsychology, 15,* 115–127.

Prabhakaran, V., Smith, J. A. L., Desmond, J. E., Glover, G. H., & Gabrieli, J. D. (1997). Neural substrates of fluid reasoning: An fMRI study of neocortical activation during performance of the Raven's Progressive Matrices Test. *Cognitive Psychology, 33,* 43–63.

Pretz, J. E., Naples, A. J., & Sternberg, R. J. (2003). Recognizing, defining, and representing problems. In J. E. Davidson & R. J. Sternberg (Eds.), *The psychology of problem solving* (pp. 3–30). New York: Cambridge University Press.

Raven, J. C. (1998). *Raven's Progressive Matrices.* San Antonio, TX: Psychological Corporation.

Rijsdijk, R. V., & Boomsba, D. I. (1997). Genetic mediation of the correlation between peripheral nerve conduction velocity and IQ. *Behavioral Genetics, 27,* 87–98.

Rolls, E. T. (1999). *The brain and emotion.* Oxford, England: Oxford University Press.

Rosenthal, R. (1990). How are we doing in soft psychology? *American Psychologist, 45,* 775–777.

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

Rothstein, M. G., Paunonen, S. V., Rush, J. C., & King, G. A. (1994). Personality and cognitive ability predictors of performance in graduate business school. *Journal of Educational Psychology, 86,* 516–530.

Sakai, K., Hikosaka, O., Miyauchi, S., Takino, R., Sasaki, Y., & Putz, B. (1998). Transition of brain activation from frontal to parietal areas in visuomotor sequence learning. *Journal of Neuroscience, 18,* 1827–1840.

Salgado, J. F. (1997). The five factor model of personality and job performance in the European community. *Journal of Applied Psychology, 82,* 30–43.

Schank, R. C., & Abelson, R. P. (1977). *Scripts, plans, goals, and understanding: An inquiry into human knowledge structures.* Hillsdale, NJ: Erlbaum.

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.

Séguin, J. R., Nagin, D., Assaad, J., & Tremblay, R. E. (2004). Cognitive-neuropsychological function in chronic physical aggression and hyperactivity. *Journal of Abnormal Psychology, 113,* 603–613.

Séguin, J. R., Pihl, R. O., Harden, P. W., Tremblay, R. E., & Boulerice, B. (1995). Cognitive and neuropsychological characteristics of physically aggressive boys. *Journal of Abnormal Psychology, 104,* 614–624.

Shariff, A., & Peterson, J. B. (2005). Anticipatory consciousness, Libet's veto, and a close-enough theory of free will. In R. D. Ellis & N. Newton (Eds.), *Consciousness and emotion: Agency, conscious choice and selective perception* (pp. 197–215). New York: John Benjamins.

Silverstein, A. B. (1982). Two- and four-subtest short forms of the Wechsler Adult Intelligence Scale—Revised. *Journal of Consulting and Clinical Psychology, 50,* 415–418.

Sternberg, R. J. (1999). The theory of successful intelligence. *Review of General Psychology, 3,* 292–316.

Sternberg, R. J. (2003). Our research program validating the triarchic theory of successful intelligence: Reply to Gottfredson. *Intelligence, 31,* 399–413.

Stuss, D. T., & Benson, D. F. (1986). *The frontal lobes.* New York: Raven Press.

Süβ, H.-M., Oberauer, K., Wittmann, W. W., Wilhelm, O., & Schulze, R. (2002). Working-memory capacity explains reasoning ability—and a little bit more. *Intelligence, 30,* 261–288.

Tellegen, A., & Briggs, P. F. (1967). Old wine in new skins: Grouping Wechsler subtests into new scales. *Journal of Consulting Psychology, 31,* 499–506.

Thompson, P. M., Cannon, T. D., Narr, K. L., van Erp, T., Poutanen, V. P., Huttunen, M., et al. (2001). Genetic influences on brain structure. *Nature Neuroscience, 4,* 1253–1258.

Thompson, P. M., Cannon, T. D., & Toga, A. W. (2002). Mapping genetic influences on brain structure. *Annals of Medicine, 34,* 523–526.

Toga, A. W., & Thompson, P. M. (2005). Genetics of brain structure and intelligence. *Annual Review of Neuroscience, 28,* 1–23.

Turner, D. C., Aitken, M. R., Shanks, D. R., Sahakian, B. J., Robbins, T. W., Schwarzbauer, C., et al. (2004). The role of the lateral frontal cortex in causal associative learning: Exploring preventative and superlearning. *Cerebral Cortex, 14,* 872–880.

Ward, L. C., & Ryan, J. J. (1996). Validity and time savings in the selection of short forms of the Wechsler Adult Intelligence Scale—Revised. *Psychological Assessment, 8,* 69–72.

Wechsler, D. (1981). *WAIS–R manual: Wechsler Adult Intelligence Scale—Revised.* New York: Psychological Corporation.

Wechsler, D. (1997). *Wechsler Adult Intelligence Scale—Third Edition (WAIS–III*). San Antonio, TX: Psychological Corporation.

Wiegersma, S., van der Scheer, E., & Human, R. (1990). Subjective ordering, short-term memory, and the frontal lobes. *Neuropsychologia, 28,* 95–98.

Wiener, N. (1961). *Cybernetics, or, Control and communication in the animal and the machine* (2nd ed.). Cambridge, MA: MIT Press.

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