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Fluid ability, crystallized ability, and performance across multiple domains: a meta-analysis

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FLUID ABILITY, CRYSTALLIZED ABILITY, AND PERFORMANCE ACROSS

MULTIPLE DOMAINS: A META-ANALYSIS

by

Bennett Eugene Postlethwaite

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Business Administration
in the Graduate College of
The University of Iowa

July 2011

Thesis Supervisor: Professor Frank L. Schmidt

Cognitive ability is one of the most frequently investigated individual differences in management and psychology. Countless studies have demonstrated that tests measuring cognitive ability or intelligence predict a number of important real-world outcomes such as academic performance, vocational training performance, and job performance. Although the relationship between intelligence and real-world performance is well established, there is a lack of consensus among scholars with regard to how intelligence should be conceptualized and measured. Of the more traditional theories of intelligence, two perspectives are particularly dominant: the Cattell-Horn model of fluid and crystallized intelligence and the theory of General Cognitive Ability (GCA or *g*).

Fluid ability (Gf) represents novel or abstract problem solving capability and is believed to have a physiological basis. In contrast, crystallized ability (Gc) is associated with learned or acculturated knowledge. Drawing on recent research in neuroscience, as well as research on past performance, the nature of work, and expert performance, I argue that compared to measures of fluid ability, crystallized ability measures should more strongly predict real-world criteria in the classroom as well as the workplace.

This idea was meta-analytically examined using a large, diverse set of over 400 primary studies spanning the past 100 years. With regard to academic performance, measures of fluid ability were found to positively predict learning (as measured by grades). However, as hypothesized, crystallized ability measures were found to be superior predictors of academic performance compared to their fluid ability counterparts. This finding was true for both high school and college students.

Likewise, similar patterns of results were observed with regard to both training performance and job performance. Again, crystallized ability measures were found to be

better predictors of performance than fluid measures. This finding was consistent at the overall level of analysis as well as for medium complexity jobs. These findings have important implications for both intelligence theory and selection practice.

Contemporary intelligence theory has placed great emphasis on the role of fluid ability, and some researchers have argued that Gf and g are essentially the same construct. However, the results of this study, which are based on criterion-related validities rather than factor-analytic evidence, demonstrate that Gc measures are superior predictors in comparison to Gf measures. This is contrary to what one would expect if Gf and g were indeed the same construct. Rather, the findings of this study are more consistent with General Cognitive Ability theory, which predicts that Gc indicators will be the best predictors of future learning and performance.

Given that Gc measures demonstrate higher criterion-related validities than Gf measures, Gc measures are likely to be preferred for selection purposes. Further, Gf scores are known to decline with age while Gc scores remain relatively stable over the lifespan. Thus, when used for selection purposes, Gf tests may underpredict the performance of older workers. In contrast, research has shown that Gc measures are predictively unbiased. Additional implications for theory and practice are discussed, along with study limitations and opportunities for future research.

Abstract Approved: _____
                                    Thesis Supervisor

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                                    Title and Department

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                                    Date

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Graduate College
The University of Iowa
Iowa City, Iowa

CERTIFICATE OF APPROVAL

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PH.D. THESIS

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This is to certify that the Ph.D. thesis of

Bennett Eugene Postlethwaite

has been approved by the Examining Committee
for the thesis requirement for the Doctor of Philosophy
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For Sandra Jane White (1943 – 2011)

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Tamara Giluk's involvement with this project predates my own. Throughout the entire study, Tamara's assistance has been invaluable. Tamara played a key role during the literature search phase, and she spent many long days coding data. I look forward to our continued collaboration in the future.

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ABSTRACT

Cognitive ability is one of the most frequently investigated individual differences in management and psychology. Countless studies have demonstrated that tests measuring cognitive ability or intelligence predict a number of important real-world outcomes such as academic performance, vocational training performance, and job performance. Although the relationship between intelligence and real-world performance is well established, there is a lack of consensus among scholars with regard to how intelligence should be conceptualized and measured. Of the more traditional theories of intelligence, two perspectives are particularly dominant: the Cattell-Horn model of fluid and crystallized intelligence and the theory of General Cognitive Ability (GCA or g).

Fluid ability (Gf) represents novel or abstract problem solving capability and is believed to have a physiological basis. In contrast, crystallized ability (Gc) is associated with learned or acculturated knowledge. Drawing on recent research in neuroscience, as well as research on past performance, the nature of work, and expert performance, I argue that compared to measures of fluid ability, crystallized ability measures should more strongly predict real-world criteria in the classroom as well as the workplace.

This idea was meta-analytically examined using a large, diverse set of over 400 primary studies spanning the past 100 years. With regard to academic performance, measures of fluid ability were found to positively predict learning (as measured by grades). However, as hypothesized, crystallized ability measures were found to be superior predictors of academic performance compared to their fluid ability counterparts. This finding was true for both high school and college students.

Likewise, similar patterns of results were observed with regard to both training performance and job performance. Again, crystallized ability measures were found to be better predictors of performance than fluid measures. This finding was consistent at the overall level of analysis as well as for medium complexity jobs. These findings have important implications for both intelligence theory and selection practice.

Contemporary intelligence theory has placed great emphasis on the role of fluid ability, and some researchers have argued that Gf and g are essentially the same construct. However, the results of this study, which are based on criterion-related validities rather than factor-analytic evidence, demonstrate that Gc measures are superior predictors in comparison to Gf measures. This is contrary to what one would expect if Gf and g were indeed the same construct. Rather, the findings of this study are more consistent with General Cognitive Ability theory, which predicts that Gc indicators will be the best predictors of future learning and performance.

Given that Gc measures demonstrate higher criterion-related validities than Gf measures, Gc measures are likely to be preferred for selection purposes. Further, Gf scores are known to decline with age while Gc scores remain relatively stable over the lifespan. Thus, when used for selection purposes, Gf tests may underpredict the performance of older workers. In contrast, research has shown that Gc measures are predictively unbiased. Additional implications for theory and practice are discussed, along with study limitations and opportunities for future research.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Background

Intelligence is one of the most frequently investigated individual differences in psychology (Brody, 1992, Fancher, 1985). Countless studies have demonstrated that tests measuring cognitive ability or intelligence predict a number of important real-world outcomes such as academic performance (e.g., Kuncel & Hezlett, 2007; Kuncel, Hezlett, & Ones, 2001, 2004; Sackett, Borneman, & Connelly, 2008), vocational training performance (e.g., Ree & Earles, 1991; Schmidt & Hunter, 1998), and job performance (e.g., Hunter, 1986; Hunter & Hunter, 1984; Salgado, Anderson, Moscoso, Bertua, & de Fruyt, 2003; Schmidt & Hunter, 1998).

That intelligence predicts performance in multiple domains is not the opinion of a select few researchers, but rather reflects the view of mainstream psychological science, as evidenced by the findings of expert panels and task forces (e.g., Neisser et al, 1996). For example, with regard to job performance, Schmidt (2002) argues that "given the overwhelming research evidence showing the strong link between general cognitive ability (GCA[1]) and job performance, it is not logically possible for industrial-organizational (I/O) psychologists to have a serious debate over whether GCA is important for job performance."

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[1] Note: General Cognitive Ability (GCA), General Mental Ability (GMA), and *g* are used interchangeably in this study.

Although the relationship between intelligence and real-world performance is well established, there is a lack of consensus among scholars with regard to how intelligence should be conceptualized and measured. Given the complex and ubiquitous nature of intelligence, such lack of consensus is not surprising. While developmental and biological approaches have been taken, psychometric approaches have been particularly dominant (Neisser et al., 1996). A survey of the literature reveals that approaches to understanding intelligence are incredibly diverse. For example, Sternberg (1988; Sternberg et al., 2000) emphasizes the importance of "practical intelligence," Gardner (1983) argues for the existence of multiple "intelligences," and Goleman (1995) advocates the concept of "emotional intelligence." Of the more traditional theories of intelligence, two perspectives are particularly dominant: the Cattell-Horn model of fluid and crystallized intelligence (Gf-Gc Theory: e.g., Cattell, 1943, 1971, 1987; Horn, 1965, 1968; Horn & Cattell, 1966) and the theory of General Cognitive Ability (GCA or *g*: e.g., Jensen, 1998; Spearman, 1904). Each of these perspectives is examined in turn.

<u>The Cattell-Horn Theory of</u>
<u>Fluid and Crystallized Intelligence</u>

As part of a long-standing program examining cognitive ability, Raymond Cattell (1941, 1943) proposed that intelligence is not a unitary construct (such as Spearman's *g*), rather it assumes two broad but distinct types, fluid intelligence (Gf) and crystallized intelligence (Gc). Cattell's doctoral student John Horn was actively involved in refining and empirically testing Gf-Gc theory and in recognition of his efforts the theory is now referred to as the Cattell-Horn theory of intelligence. Gf-Gc theory has found wide acceptance among cognitive ability researchers. For example, Caroll (1993, p. 62) argues

that the Cattell-Horn model "appears to offer the most well-founded and reasonable approach to an acceptable theory of the structure of cognitive abilities."

Fluid Intelligence

According to the theory, fluid intelligence represents novel or abstract problem solving capability and is believed to have a physiological basis. According to Cattell (1987, p. 97), the label reflects the construct's "'fluid" quality of being directable to almost any problem." Gf is typically assessed with items of a nonverbal or graphical format using tests such as Raven's Progressive Matrices (see Figure 1 for an example item). However, verbal items (such as analogies) can also be used to assess Gf if the word pairs contain simple words that are familiar to the population of test takers (Cattell, 1987; Jensen, 1998). Figure 2 provides an example of such an item. Examples of some tests commonly used to measure Gf are presented in the left column of Table 1.

Crystallized Intelligence

Crystallized intelligence is associated with learned or acculturated knowledge. That is, Gc is a result of learning and knowledge acquired over one's lifetime. According to Gf-Gc theory, fluid intelligence causes crystallized intelligence. More specifically, Cattell's (1971, 1987) Investment Theory proposes that individuals have a fixed amount of Gf which they can choose to "invest" in, or apply to, learning in specific "crystallized skills" or domains. Gc is typically measured with verbal items, particularly those assessing vocabulary. Figures 3 and 4 provide examples of items designed to assess

crystallized intelligence. Examples of some tests commonly used to measure Gc are presented in the center column of Table 1.

As Carroll (1993) notes, Gf and Gc are in fact correlated. While some scholars view this as evidence for the higher level construct of g (Ackerman, Beier, & Boyle, 2005), traditional Gf-Gc theorists choose not to extract the general factor, a choice that reflects their view that g is merely a statistical artifact rather than a meaningful psychological construct (Hunt, 2000).

General Cognitive Ability

The theory of general cognitive ability (g) provides an alternative to Gf-Gc theory. Following Spearman (1904), g theorists (e.g., Gottfredsen, 1997; Jensen, 1998) advocate a single, top-level intelligence construct. This is represented by a single general factor g, which is a latent variable that causes the correlations between different measures of cognitive ability. That is, g refers to the shared variance between cognitive ability measures, or rather what different measures of ability share in common. A number of scholars have attempted to interpret g in terms that are less statistical in nature. For example, Ackerman and colleagues (2005, p. 32) describe g as "a generic representation for the efficiency of intellectual processes." Gottfredsen (1997, p. 79) argues that g is "essentially the ability to deal with cognitive complexity, in particular, with complex information." Schmidt and Hunter maintain that general cognitive ability is "essentially the ability to learn" (Hunter, 1986; Hunter & Schmidt, 1996; Schmidt, 2002, p. 188). Although these definitions vary to some extent, each represents g as a cognitive construct
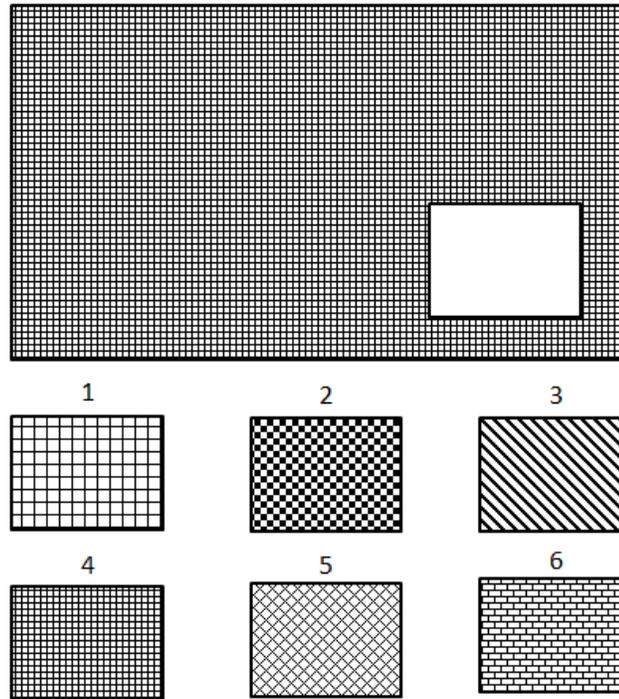
Figure 1. Example of a Simple Graphical Item Used to Assess Gf

Source: Adapted from Figure A5 of Raven's Standard Progressive Matrices (Raven, 1938; original item A5 reprinted in Greenfield, 2009, p. 69, Figure 1)

Temperature is to **cold** as **Height** is to

 (a) hot
 (b) inches
 (c) size
 (d) tall
 (e) weight
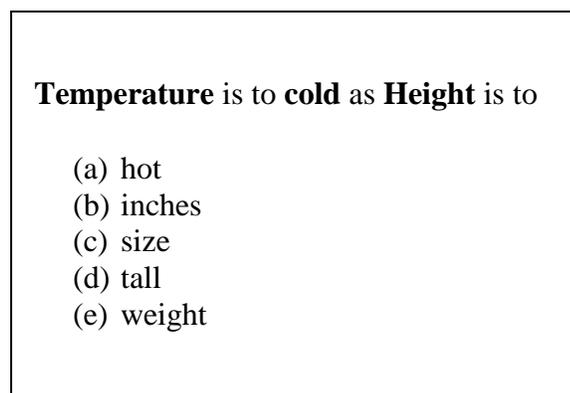
Figure 2. Example of a Verbal Analogy Item Used to Assess Gf

Source: Adapted from Jensen (1998, p.123)

PRESENT/RESERVE, Do these words:

    a) have similar meanings;
    b) have contradictory meanings
    c) mean neither the same nor opposite?
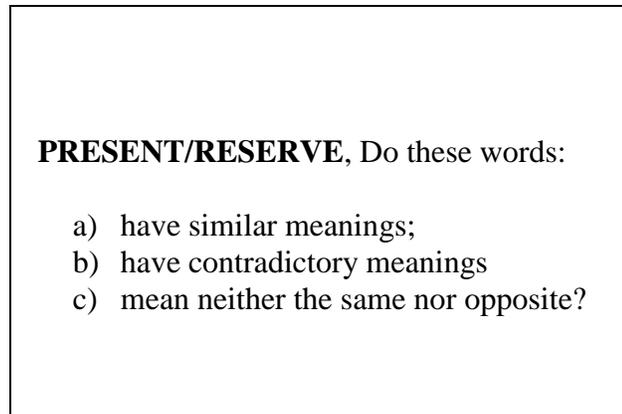
Figure 3. Example of a Question Assessing Gc

Source: Sample item from the Wonderlic Personnel Test

Bizet is to **Carmen** as **Verdi** is to

    (a) Aida
    (b) Elektra
    (c) Lakme
    (d) Manon
    (e) Tosca
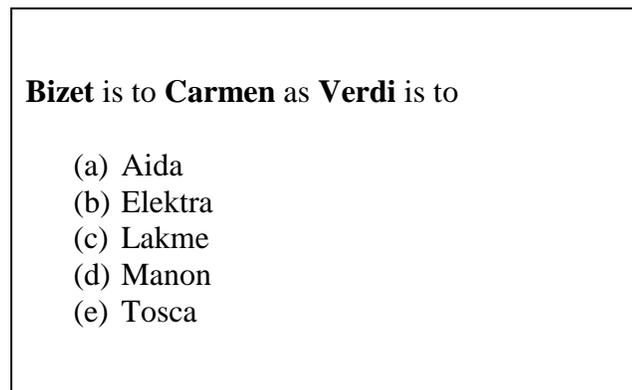
Figure 4. Example of a Question Assessing Gc

Source: Adapted from Jensen (1998, p. 123)

Table 1. Common Tests Used to Measure Gf, Gc, and GCA

Fluid Ability (Gf) Tests	Crystallized Ability (Gc) Tests	General Cognitive Ability (GCA) Tests
• Raven's Standard Progressive Matrices • Raven's Advanced Progressive Matrices • Culture Fair Intelligence Test • Differential Aptitude Test (Abstract Reasoning)	• ACT • SAT • Mill Hill Vocabulary Test • Armed Services Vocational Aptitude Battery (ASVAB) • General Aptitude Test Battery (GATB)	• Wonderlic Personnel Test • Otis Quick-Scoring Test of Mental Ability • Stanford-Binet Intelligence Test • Wechsler Adult Intelligence Scale

that is broader in scope than either Gf or Gc. Further, viewed from the perspective of Gf – Gc theory, GCA tests are combinations of Gf and Gc measures. Examples of some tests commonly used to measure general cognitive ability are presented in the right column of Table 1.

Most *g* theorists do not deny the existence of Gf and Gc; however, they maintain that Gf and Gc are merely different kinds of indicators of the higher-order latent variable *g*. The larger and more diverse the number of indicators used, the more construct valid will be the final estimate of *g*. Because Gf and Gc are different indicators, they have unique properties (e.g., Gf indicators decline more with age than Gc indicators; Gc indicators better assess past use of *g* to learn skills and knowledge).

As stated previously, Gc tests measure how well a person has learned a wide variety of things in the past. A fundamental principle in psychology is that past behavior is the best predictor of future behavior (Oullette & Wood, 1998). Thus, when defining *g* as *the ability to learn*, *g* theory predicts that Gc indicators will be the best predictors of future learning and performance (which depends on learning).

Study Purpose & Method

Previous studies have typically examined Gf and Gc using factor analysis. Although factor analysis can be informative, it can also be problematic in that results can vary substantially depending on the specific combinations of tests examined. For example, Hunt (2000) points out that it is possible (and indeed quite simple) to manipulate the extraction of a general factor by selecting certain combinations of tests to analyze. That is, "interpretation of any summarizing statistic, including a general factor, depends upon what is being summarized" (Hunt, 2000, p. 126). More importantly, although factor analysis can help distinguish the statistical structure of constructs such as Gf and Gc (Hunt, 2000), it offers no information with regard to the ability of those constructs to predict real-world outcomes. Given that cognitive tests are used in a number of high-stakes employment, admissions, and educational placement decisions, it is imperative to assess the criterion-related validity of these tests.

Accordingly, it is beneficial to examine the usefulness of Gf and Gc measures using an alternate methodology. Meta-analysis is an ideal tool for this task as it is a robust statistical method for synthesizing quantitative research results from multiple studies (Hunter & Schmidt, 2004). Likewise, meta-analysis can correct for the biasing

effects of sampling error, measurement error, and range restriction inherent in individual primary studies. The results of meta-analytic investigations can be highly informative. Meta-analysis can be used to examine relationships between constructs (such as the strength of correlation between Gf and Gc). For example, Ackerman and colleagues (2005) recently used meta-analysis to dispel a widely held belief that working memory and intelligence are isomorphic constructs. After correcting for measurement error and sampling error (but not range restriction), they estimated that the correlation between working memory and g was less than unity ($\bar{\rho} = .479$).

Meta-analysis is also frequently used to examine a measure's predictive validity. A number of previous meta-analyses have examined the criterion-related validity of various cognitive ability measures, particularly general cognitive ability (g or GCA; e.g., Bertua, Anderson, & Salgado, 2005; Hülsheger, Maier, & Stumpp, 2007; Hunter, 1986; Hunter & Hunter, 1984; Ree & Earles, 1991; Salgado et al., 2003a; Schmidt & Hunter, 1998), with each study finding a strong correlation between GCA and performance criteria. However, the criterion-related validities of fluid and crystallized measures have yet to be separately meta-analyzed and compared with each other or to the validity of omnibus GMA measures. Furthermore, the majority of previous meta-analyses were conducted prior to the recent development of advanced methods which allow for the correction of indirect range restriction (Hunter, Schmidt, & Le, 2006; Le, 2003; Le & Schmidt, 2006; Schmidt, Oh, & Le, 2006).

In this study, I meta-analyze a large number of published and unpublished primary studies that have examined the relationship between measures of intelligence (Gf, Gc, or GCA) and at least one of three types of performance criteria: academic

performance, vocational/training performance, and job performance. The results of these meta-analyses provide quantitative evidence to address the question of whether fluid or crystallized measures are stronger predictors of future learning and performance.

<u>Value to Management & Applied Psychology</u>

By estimating and comparing the criterion-related validities of Gf, Gc, and GCA, this study makes an important contribution to our cumulative knowledge regarding intelligence and real-world performance. The findings will have implications for theory as well as practice.

Organizations have a continual need to identify and select the individuals who are most likely to be successful when hired (or accepted to an academic program). Indeed, research has shown that even seemingly small increases in test validity can yield substantial utility through increases in future production and performance (Schmidt & Hunter, 1998). Since Gf and Gc measures are both used for selection purposes, it is important for decision makers to understand which measures are the better predictor of future performance. In a recent review of crystallized intelligence, Hunt (2000, p. 126) provides additional impetus for why it is important to estimate the validity of Gf and Gc measures used for selection purposes:

> I suspect strongly that many of the tests in common industrial use
> also have a heavy Gc loading. This is probably the case for the
> tests used in the studies reviewed by Schmidt and Hunter (1998),
> and which provided evidence for the general factor measure as a
> predictor of job performance.

Hunt bases his argument in part on Roberts et al.'s (2000) finding that the Armed Services Vocational Aptitude Battery (ASVAB) primarily measures Gc rather than Gf.

Likewise, McGrew (1997) evaluated the content of major intelligence batteries using the Gf-Gc framework. He concluded crystallized and visual/spatial (Gv) abilities were the most frequently represented abilities, while pure measures of Gf were much less common. Validities for intelligence batteries are often reported at the overall or composite level, and this validity is a function of the validities of the constituent scales. If there is indeed an imbalance in the representation of Gf and Gc in current intelligence assessments, it is especially important to understand the predictive validity of each construct as these validities will impact overall test validity.

In addition, scientists have made important observations regarding patterns of change in intelligence scores both within individuals and between cohorts of individuals over time. These findings provide additional motivation to investigate the criterion-related validity of Gf and Gc measures. First, large increases in intelligence scores have been observed within cohorts of test takers over the past century. This phenomenon has become known as the Flynn effect (e.g., Flynn, 1987). Flynn observed that IQ scores appear to have risen an average of 20 points per generation (i.e., every 30 years; Flynn, 1998). However, a closer look at the data reveals increases are visible primarily in Gf measures (such as the Raven's Progressive Matrices) and not in Gc measures (such as the SAT verbal scores) (Flynn, 1987, 1998; Raven, 2000). Meta-analytic results can contribute to the discussion as to whether Gf score increases are real or artifactual.

Furthermore, it is widely established that cognitive ability declines to some extent with age (Brody, 1992; Schaie, 1994; Verhaeghen & Salthouse, 1997). Although some of the research in this area has appeared conflicting, Hough and colleagues (2001) maintain that "seemingly conflicting data regarding the relationship between age and

cognitive ability become consistent and interpretable when cognitive abilities are grouped according to crystallized and fluid intelligence" (p. 159-160; see also Horn & Donaldson, 1976). This is due to that fact that rates of cognitive decline are quite different for Gf vs. Gc. The largest declines are seen with measures of fluid intelligence. In contrast, crystallized intelligence remains relatively stable until an extremely advanced age. Cattell proposed this general pattern of results in his early (1943) presentation of Gf-Gc theory. Some organizations use fluid assessments for selection purposes because the tests are thought to reduce adverse impact towards underrepresented groups (due to a lack of culturally-biased test content) and non-native speakers (due to a lack of verbal content), although not all researchers agree with such characterizations (e.g., Greenfield, 1998). However, because fluid intelligence declines with age, using Gf measures for selection may also have the unintended consequence of adversely impacting older workers (c.f., Hough et al., 2001). This may be particularly problematic given the increasingly aging workforce. The problem is likely to be exacerbated if Gf measures are found to be less valid predictors of performance than Gc measures. This underscores the need to develop a better understanding of the relationship between Gf, Gc, and performance.

Overview of Subsequent Chapters

This study unfolds as follows:

Chapter 2 provides a review of the literature on cognitive ability and performance. The historical background and contemporary state of Gf-Gc and *g* theory are discussed.

Hypotheses are developed in Chapter 3. In particular, I draw on the relevant research that has examined past performance, the nature of work, expert performance, and the relationship between age and job performance.

Chapter 4 provides details on the meta-analytic methodology to be employed. This includes details on the comprehensive literature search strategy, classification of cognitive ability measures according to Gf-Gc theory, coding of studies, and correction for artifacts such as criterion unreliability and range restriction.

The results of the study are presented in Chapter 5. The findings are discussed in Chapter 6, along with implications for theory, future research, and practice.

CHAPTER 2

LITERATURE REVIEW

<u>Chapter Overview</u>

In this chapter I review the literature on cognitive ability, placing particular emphasis on fluid and crystallized ability. I begin by discussing the historical development of intelligence testing in general, and Gf-Gc theory in specific. I then review applications of Gf-Gc theory including Cattell's (1971/1987) Investment Theory, Carroll's (1993) three-stratum model of ability, and changes in ability scores over time.

<u>The Historical Development of Intelligence Testing</u>

Philosophers and scholars have debated the nature, source, and application of cognitive abilities throughout recorded history. Likewise, the idea that cognitive abilities can and should be measured is not limited to modern times. Bowman (1989) argues that the origins of cognitive ability testing can be traced to ancient China. In approximately 150 BCE, emperors of the Qin or early Han dynasties established an examination program. Chinese examinations functioned as selection tests, providing the primary route for entry into the civil service. The degree of importance placed on these civil service examinations was such that DuBois (1965) summarily characterized China as being a "test-dominated society."

By the time of the Ming dynasty (1368-1644), the civil service examination system had become elaborate and formal, a core element of Chinese society that prevailed until the early twentieth century (Bowman, 1989; Franke, 1960). Testing was a

multistage process, with increasingly difficult tests being administered at the local

(prefectural), regional (provincial), and national (metropolitan) levels (Hanson, 1992).

By advent of the Sung dynasty (960-1279), civil service examinations were open to

nearly all Chinese, regardless of background. According to Lai (1970), there were some

individuals and their immediate descendants who were ineligible for examinations. For

example, excluded occupations included jailers, coroners, detectives, actors, musicians,

boat-people, and beggars. Nevertheless, access to the wealth and prestige afforded to the

bureaucratic elite was dependent to a large degree on merit (i.e., exam performance)

rather than parentage or family history (Hanson, 1992).

Chinese examination procedures were incredibly rigorous (Kracke, 1953;

Miyazaki, 1981). Examinations were broad in scope, consisting of essays on classics,

history, and politics. To insure fairness, tests were marked by at least two examiners.

Further, in an attempt to maintain anonymity, examination scripts were "identified only

by number and reproduced by professional copyists to prevent identification of the author

by name or distinctive calligraphy" (Hanson, 1992, p. 190). Miyazaki (1981) provides a

fascinating account of the extreme measures that were taken to maintain test security in

one southern province. During examination periods, candidates were placed in small cells

within specially-constructed walled compounds for three days and two nights. Gates to

the compound were latched and sealed and were not to be opened under any

circumstance. The level of security was such that if a candidate died during the

examination, his body was thrown over the compound wall.

After the Boxer Rebellion (1898-1901), the Chinese government announced plans

for a new system of education. As a result, traditional civil service examinations were

formally abolished in 1905. Nevertheless, Hanson (1992, p. 191) concludes that given its "amazing persistence, together with the central role it played in imperial Chinese society, the Chinese civil service examination must certainly be credited as the most successful system of testing the world has ever known."

While ability testing played a central role in ancient China, it was certainly not absent in the ancient West. For example, Doyle (1974, p. 202) argues that "ancient Greece, if not a test-dominated society, was certainly a test-influenced one." Although ancient Greeks placed a heavy emphasis on physical ability testing, they also engaged in achievement and mental aptitude testing (Doyle, 1974; Freeman, 1912; Marrou, 1956). Further, Greek philosophers theorized about mental abilities as well as the utility of tests designed to measure them. Doyle maintains that Plato's view of ability testing was based on his belief in individual differences. In his *Republic*, Plato (428/7-348/7 BCE) argues that "we are not all alike; there are diversities of natures among us which are adapted to different occupations" (*Republic* 370, p. 48-49). Consequently, "all things are produced more plentifully and easily and of a better quality when one man does one thing which is natural to him" (*Republic* 370, p. 49).

Several scholars (e.g., Deary, 2000; Detterman, 1982; Shields, 1975) have credited Juan Huarte de San Juan (*c.* 1530-1592), a Spanish physician, with having made the first extensive theoretical examination of individual differences in cognitive ability. In 1575, Huarte published *Examen de ingenios para las ciencias* (*The examination of men's wits*). In his book, Huarte argues that men differ in "wits" (or cognitive abilities). These differences are proposed to be biological in nature, and in turn have implications for the types of education and occupations to which individuals are suited. For example,

> before I received any scholar into my schoole, I would grow to many trials and experiments with him, until I might discover the qualite of his wit, and if I found it by nature directed to that science whereof I made profession, I would willingly receive him, for it breeds a great contentment in the teacher to instruct one of good towardliness: and if not, I would counsaile him to studie that science, which were most agreeable with his wit. But if I saw that he had no disposition or capacitie for any form of learning, I would friendly and with gentle words tell him; brother, you have no means to prove a man of that profession which you have undertaken, take care not to loose your time or your labour, and provide you some other trade or living, which requires not so great an habilitie as appertaineth to learning. (Huarte, 1575, p. 4).

Huarte's basic view of individual differences in cognitive ability echoes that of Plato, whose work he reviews in *Examen de ingenios,* along with that of other ancient scholars including Socrates (*c.* 470-399 BCE), Hippocrates (*c.* 460-*c.* 377 BCE.), Aristotle (384-322 BCE), and Galen (129-216). However, Huarte developed his theory of cognitive abilities in considerably more depth than earlier scholars. Of particular interest is his distinction between imagination- and memory-based problem solving, which Hunt (2011) maintains is analogous to Cattell's distinction between fluid and crystallized ability. Hunt notes that Cattell developed Gf-Gc theory independently of Huarte, whose work was largely forgotten until being reintroduced by Spanish psychologists during the 1980s.

Many scholars attribute the advent of contemporary ability testing to the work of British polymath Francis Galton (1822 – 1911). A half-cousin of Charles Darwin, Galton made a number of significant contributions in diverse areas including geography and travel (Galton, 1853; Galton, 1855), meteorology (Galton, 1863), fingerprint analysis (1892), and statistics (Galton, 1888). Galton was heavily influenced by Darwin's (1859) *On the Origin of Species,* and he believed that Darwin's theory of natural selection could be fruitfully applied to the domain of human cognitive abilities. Accordingly, Galton

(1865, 1869) presented evidence suggesting that intellectual ability was hereditary in nature. A consequence of this, Galton believed, was that human intellectual stock could be improved by encouraging persons of the highest intellectual ability to mate and produce offspring. However, to enact such a plan would require some standardized method for identifying persons of high ability. Galton (1865, p. 165) proposed that this might be accomplished using "a system of competitive examinations," and he later went on to adopt and develop a series of tests designed to measure ability. In 1884, Galton began to administer such tests in his Anthropometric Laboratory located at the International Health Exhibition in London. After the exhibition closed, the laboratory was relocated to the nearby South Kensington Museum and the number of tests was expanded. Members of the general public each paid a small fee to complete various tests designed to measure physical characteristics (height, weight, arm span, eye color), muscular strength, reaction time, and sensory acuity (vision, line and weight perception, hearing/tone perception) (Galton, 1883, 1888). Several scholars (e.g., Carroll, 1982; Wasserman and Tulsky, 2005) have noted that of all the tests used by Galton, only the digit span test (Jacobs, 1887) is still used by psychologists.

Galton's approach to measuring mental ability was enthusiastically adopted by James McKeen Cattell[2] (1860 – 1944), an American psychologist who had studied under Wilhelm Wundt. In an 1890 paper, Cattell describes ten tests for measuring mental ability, a number of which had been used by Galton. These included dynamometer pressure, sensation areas, reaction time for sound, weight differentiation, and bisection of

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[2] Note: James McKeen Cattell should not be confused with Raymond Cattell. The two psychologists were not related.

a 50 cm line, among others. However, Cattell's enthusiasm for this approach dampened after Clark Wissler published a study (Wissler, 1901) that suggested Cattell's mental tests were correlated neither with each other, nor with student grades. Wissler, a graduate student of Cattell's at Columbia University, based his findings on a large sample of undergraduate students at Columbia. A similar conclusion was reached by Stella Sharp (1898-1899), a graduate student at Cornell working under Titchener.

Wissler's (1901) and Sharp's (1898-1899) studies have often been cited as having dealt a fatal blow to efforts to measure intelligence using measures of sensory discrimination (c.f., Boring, 1950; Carroll, 1982; Eckberg, 1979; Fancher, 1985). However, Deary (2000) is highly critical of such characterizations. He maintains both studies were flawed. For example, Wissler's results were based on a highly range-restricted sample (students at one of the country's premier universities). Further, Wissler calculated less than 10% of all of the possible correlation coefficients in the data set (Jensen, 1980, p. 139-140). Sharp's conclusions were based on a sample of only *seven* graduate students, hardly a sufficient sample size to make a definitive conclusion.

An alternate approach to measuring intelligence was developed by French psychologist Alfred Binet (1857 – 1911) and his colleagues. Binet was skeptical of attempts to assess intelligence using only sensory measures. Five years prior to the publication of Wissler's (1901) paper, Binet and Henri (1896) argued that

> if one wishes to study the differences existing between two individuals it is necessary to begin with the most intellectual and complicated processes, and it is only a second line that one must consider the simple and elementary processes; it is, however, just the opposite which is done by the great majority of authors who have taken up this question (p. 417; translation cited in Fancher, 1985, p. 67)

Using an inductive approach, Binet and his graduate student Theodore Simon (1873 – 1961) worked to develop a battery of scales (Binet & Simon, 1905a, 1905b, 1905c) to assess the degree to which French schoolchildren were developmentally-delayed for their ages. While other researchers focused on simple reaction measures, Binet and Simon found that scales assessing more complex abilities such as imagination, verbal fluency, memory, and judgment permitted better discrimination between high and low performing students. Thus, they concluded that "to judge well, to comprehend well, to reason well, these are the essential ingredients of intelligence" (Binet & Simon, 1905b, p. 197, translation cited in Mackintosh, 1998, p. 13).

Binet and Simon's intelligence scales had enormous impact. According to Mackintosh (1998), the scales "formed the basis of modern IQ tests…and became the norm against which later tests were judged" (p. 14). The scales were translated into English and adapted for use in the United Kingdom by Cyril Burt (Burt, 1921) and in the United States by Lewis Terman, a Stanford University psychologist (Terman, 1916; Terman & Childs, 1912; Terman & Merrill, 1937). The Stanford-Binet remained the dominant intelligence test until the release of the Wechsler scales (e.g., Wechsler, 1939) (Mackintosh, 1998). Nevertheless, the Stanford-Binet continues to be published and is currently in its fifth edition (SB5).

Mackintosh (1998) notes that the Stanford-Binet, and the Wechsler scales which followed, are individual intelligence tests. As such, they are administered by a trained psychological examiner to one client at a time. While this allows for an in-depth assessment, it proves costly and inefficient if a large number of individuals need to be tested. This was the case during World War I. The war brought a strong desire to apply

psychological principles to aid the war effort. Robert Yerkes (1876 – 1956), then president of the American Psychological Association and chairman of the Committee on the Psychological Examination of Recruits, led an effort to develop group intelligence tests which could be administered to large numbers of U. S. Army recruits. The resulting tests, the *Army Alpha* for literate recruits and the *Army Beta* for illiterate recruits, were administered to nearly 1.7 million men by the end of the war (Ackerman, 1996; Fancher, 1985). According to Ackerman, "the Army Alpha Test (and, to some degree the nonverbal Army Beta Test) stand out as the vehicles for fixing the paradigm for adult ability assessment" (p. 229). Following the war, a number of group intelligence tests (e.g., the Otis-Lennon Ability Test, the Thorndike Intelligence Examination for High School Graduates, and the National Intelligence Test) became commercially available. Accordingly, the adoption of such tests for educational and occupational purposes grew rapidly (for example, see Toops, 1926). A new era of ability testing had begun.

<center>The Historical Development of Gf-Gc Theory</center>

After receiving an undergraduate degree in Chemistry from the University of London at age 19, British-born Raymond Cattell (1905-1998) decided to change course and pursue a PhD in psychology. Cattell (1974) would later recollect that his decision was based on a desire to apply science to real social problems, and he felt psychology offered the best potential for making a significant impact. Cattell studied under Charles Spearman, receiving his PhD from the University of London in 1929. In 1937, Cattell joined Columbia University as a research associate at the invitation of E. L. Thorndike. Cattell would remain in the United States for the remainder of his life, holding positions

at several institutions including Clark University, Harvard, the University of Illinois, and
the University of Hawaii.

Ackerman (1996, p. 232) rightly observes that the "origins of Cattell's (1984)
bifurcation of intelligence into fluid and crystallized domains are somewhat murky."
One notable attempt to clarify this issue was made by Carroll (1984), who traced the
historical development of Gf-Gc as part of his review of Cattell's contributions to
cognitive ability theory. Carroll notes that from the 1930's through 1950's, much of
Cattell's attention was devoted to the development of intelligence tests which emphasized
universal content rather than culturally-acquired knowledge, and "undoubtedly, the work
on 'culture-free' or 'culture-fair' tests planted the seeds for the theory of 'fluid' and
'crystallized' intelligences associated with Cattell's name" (1984, p. 302).

As early as 1933 (e.g., Cattell & Bristol, 1933), Cattell argued that the majority of
existing intelligence tests placed undue emphasis on acquired knowledge.   In 1940
Cattell described the development of a nonverbal, "culture-free" intelligence test built
upon the premise that it was indeed possible to find "among different cultural groups a
common ground of knowledge, on which operations of reasoning could be performed"
(Cattell, 1940, p. 165). The test was comprised of graphical items adapted from other
recently developed cognitive tests. These included mazes (Porteus, 1937), picture series,
item classification (Line, 1931; Spearman, 1933), progressive matrices (Penrose &
Raven, 1936), and mirror images. Cattell, Feingold, and Sarason (1941) evaluated the
test against traditional intelligence tests popular at the time such as the Binet and the
American Council of Education (ACE) Psychological Test. They found that among
groups of children and immigrants, the culture-free test displayed the highest loading on

general intelligence factor (*g*). That is, the nonverbal test items were highly *g*-saturated. However, for the educated sample (consisting primarily of teachers), traditional intelligence tests displayed higher *g*-loadings. The authors also observed reduced *g*-loadings for the culture-free test when subjects, particularly children, were retested. Cattell does not use the terms "fluid" or "crystallized" intelligence in these papers on the culture-free intelligence test (Carroll, 1984), however, it is important to note the content of the culture-free tests closely mirrors tests which Cattell and other scholars (e.g., Horn & Cattell, 1967) would later classify as pure measures of fluid intelligence (e.g., the Raven's Progressive Matrices).

Cattell's presentation at the 1940 American Psychological Meeting (Cattell, 1941) is frequently credited as his first public presentation of Gf-Gc theory (see for example, Cattell, 1979; Horn, 1968), although Carroll (1984) notes the original paper is unavailable. Gf-Gc theory appears for the first time in print in a 1943 *Psychological Bulletin* article in which Cattell reviews the state of adult intelligence testing. In this article Cattell made four assertions (p. 178) that would become the backbone of Gf-Gc theory:

(1) Adult mental capacity is of two kinds, the chief characteristics of which may be best connoted by the use of the terms "fluid" and "crystallized."

(2) Fluid ability has the character of a purely general ability to discriminate and perceive relations between any fundaments, new or old. It increases until adolescence and then slowly declines. It is associated with the action of the whole cortex. It is responsible for the intercorrelations, or general factor, found among children's tests and among the speeded or adaptation-requiring tests of adults.

(3) Crystallized ability consists of discriminatory habits long established in a particular field, originally through the operation of fluid ability, but not longer requiring insightful perception for their successful operation.

(4) Intelligence tests test at all ages are the combined resultants of fluid and crystallized ability, but in childhood the first is predominant whereas in adult life, owing to the recession of fluid ability, the peaks of performance are determined more by the crystallized abilities.

A number of scholars (e.g., Ackerman, 1996; Brody, 1992; Carroll, 1984; Horn, 1968) as well as Cattell himself (1943), have noted the similarity between Gf-Gc theory and the ideas on intelligence proposed by D. O. Hebb (1941, 1942, 1949). Hebb (1941, 1942) carefully examined the cases of individuals who had suffered brain damage at different stages of their lives. He observed that individuals who suffered brain injury as mature adults often showed little to no decrement in vocabulary or IQ after their injuries. On the other hand, infants who suffered brain injury at birth showed notably low vocabulary and IQ scores during adolescence. Hebb believed that these findings suggested that "intelligence" can have two meanings One such meaning, Intelligence A, is biological in nature. It represents "*innate potential*, the capacity for development, a fully innate property that amounts to the possession of a good brain and a good neural metabolism" (Hebb, 1949, p. 294). The second meaning, Intelligence B, is "the functioning of a brain in which development has gone on, determining *an average level of performance or comprehension* by the partly grown or mature person" (Hebb, 1949, p. 294). Brody (1992) and Carroll (1984) refer to Hebb's Intelligence A and B as "types" of intelligence akin to Cattell's Gf and Gc. Although the concepts are indeed similar, Hebb (1949, p. 294) emphasizes that Intelligence A and B "are not two parallel kinds of intelligence, coexistent, but two meanings of 'intelligence.'" In a 1968 review of Gf-Gc theory, Horn (p. 242) argues that Cattell's "Gf-Gc formulation is preferable to the Hebbian conceptualization because the principal concepts in this theory have specifiable and measurable behavioral referents, whereas in Hebb's theory intelligence A does not

refer to measurable behavior but to neurological potential." Horn's argument clearly reflects the behaviorist influences which were dominant in psychology at the time. However, such an argument appears be much less valid in contemporary times, particularly given the growing importance of cognitive psychology and the rapid developments in neuroscience which have been facilitated by new technologies such as fMRI (see for example Gray, Chabris, & Braver, 2003).

After proposing Gf and Gc in the early 1940's, Cattell proceeded to dedicate the majority of his empirical research efforts during the next two decades to the investigation of personality (e.g., Cattell, 1946, 1950, 1957, 1965) rather than intelligence. However, he did make several explications of Gf-Gc theory on selected occasions during this period (Cattell, 1950, pp. 477-491; Cattell, 1957a, pp. 871-879), in addition to revising his culture-free intelligence assessment (i.e., The IPAT Culture Fair Intelligence Scales; Cattell, 1957b).

It was not until the 1960's that Cattell began to examine Gf-Gc theory empirically. In his initial empirical effort, Cattell (1963) examined the factor structure of intelligence using a sample of 277 7th and 8th grade students who had taken the Thurstone Primary Ability Tests, the Culture Fair Intelligence Scales, and the HSPQ personality inventory. Cattell found evidence for two separate general ability factors which he subsequently labeled as Gf and Gc. While most of the Culture Fair subtests (Classification, Matrices, Topology) loaded heavily on the fluid ability factor, Thurstone Verbal, Reasoning, and Number ability tests loaded heavily on the crystallized ability factor. Though optimistic about these results, Cattell acknowledged that a thorough test of the theory would require replication using more heterogeneous samples. Specifically,

Cattell believed that the distinction between Gf and Gc would be more clearly evident in samples that were heterogeneous with respect to educational background:

> The general theory also argues that in viewing the Gf-Gc distinction from the point of view of individual differences study, it will be most clear-cut in a sample of people wherein a wide variety of background influences would have operated to produce presently measureable abilities. When educational opportunities are closely tied to capacity, as represented in Gf, the development of Gc will tend to be closely tied to the development of Gf and the distinction will be difficult to draw in empirical analyses. But when individuals differ considerably with respect to a variety of background influences, then it is likely that in many cases educational opportunities will be premised on many factors other than the capacity represented by Gf. Hence the distinction between Gf and Gc will show up most clearly wherein there is heterogeneity with respect to background variables. (Horn & Cattell, 1966, pp. 259-260).

The 1960's also marked the advent of a long-standing collaboration between Cattell and his then doctoral student John Horn (1928 – 2006). Although initially interested in personality, Horn quickly embraced the theory of fluid and crystallized intelligence. Horn continued to expand and refine Gf-Gc theory over his entire career. Accordingly, intelligence scholars now attribute the theory to both Cattell and Horn (e.g., Cattell-Horn theory). In his (1965) dissertation, Horn expanded the Gf-Gc dichotomy to include two additional ability factors, General visualization (Gv) and General speediness (Gs). Over time, additional factors were added to the model (Alfonso, Flanagan, & Radwan, 2005; McGrew, 2005). These included short-term memory (Gsm) or short-term apprehension and retrieval (SAR), long-term memory (Glm) or tertiary storage and retrieval (TSR), and auditory processing (Ga). The most recent additions to the model include correct decision speed (CDS), quantitative ability (Gq), and reading/writing ability (Grw). An overview of these abilities is presented in Figure 5 (stratum II). According to Gf-Gc theory, each of these is a

| Gf | Gq | Gc | Grw | Gsm SAR | Gv | Ga | Glm TSR | Gs | CDS | |
| Fluid intelligence | Quantitative knowledge | Crystallized intelligence | Reading/writing | Short-term memory | Visual processing | Auditory processing | Long-term retrieval | Processing speed | Correct Decision speed | **Stratum II Broad Abilities** |

Stratum I - Narrow Abilities
(Not Shown)
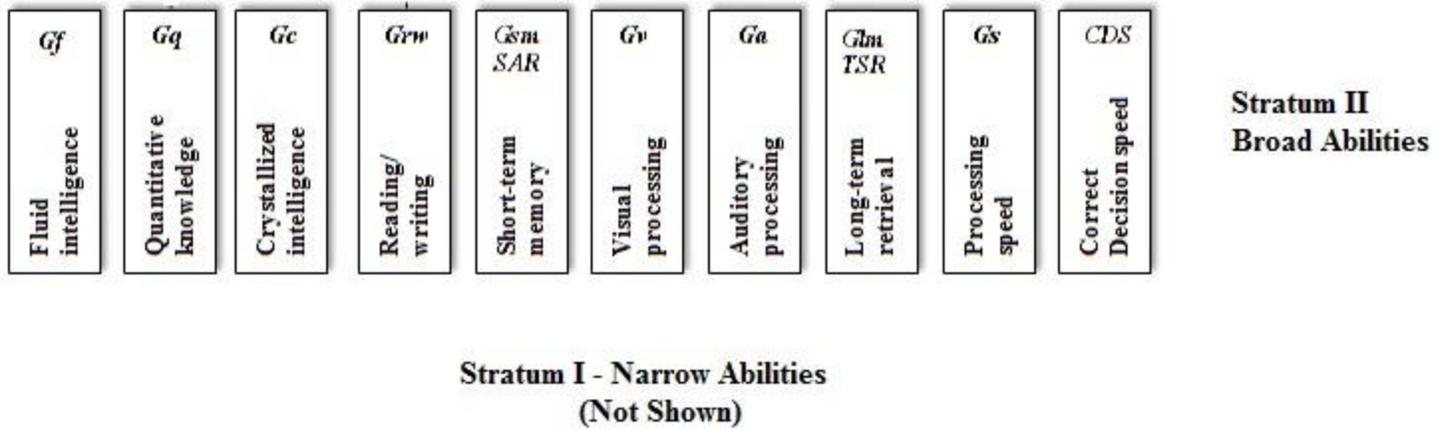
Figure 5. Cattell-Horn Two-stratum Model of Intelligence

Source: Adapted from Flanagan, Ortiz, Alfonso, & Mascolo (2002) and Alfonso, Flanagan, & Radwan (2005, p. 187, Figure 9.1)

broad, second-order (stratum II) ability factor that emerges when a large, diverse set of tests measuring narrow (stratum I) abilities are factor analyzed. Further, these broad second-order abilities are proposed to be correlated yet independent (Horn & Blankson, 2005). That is, they are believed to display differential validities with other variables such as age or performance.

<div align="center">Cattell's Investment Theory</div>

One of the core ideas underlying Gf – Gc theory is that Gf and Gc are causally related, whereby the acquisition of Gc is dependent, to a large degree, on Gf. Other factors such as personality, motivation, and educational opportunity are also proposed to impact the development of Gc, although to a lesser extent than fluid ability. A converse or reciprocal relationship is not part of the theory. That is, "level of gf is considered to be unaffected by previous gc acquisitions" (Schmidt & Crano, 1974, p. 255). Schmidt and Crano maintain that the proposed causal relationship between Gf and Gc is rather unique among major theories of intelligence. For example, the intelligence theories proposed by Thurstone (1938), Burt (1949, 1955), Vernon (1961), and Guilford (1967) do not contain causal arguments of the kind advanced by Cattell, even though some of these theories do propose the existence of factor pairs (e.g., verbal/educational vs. practical; Vernon, 1961).

Although not explicitly referred to as such, the basic principles of Investment Theory are evident in Cattell's early work on cognitive ability. For example, in his first presentation of Gf – Gc theory in a 1943 *Psychological Bulletin* article, Cattell argues that:

> Crystallized ability consists of discriminatory habits long established in a particular field, *originally through the operation of fluid ability*, but no longer requiring insightful perception for their successful operation (1943, p. 178, emphasis added).

By 1963, Cattell was explicitly referring to "investments." For example:

> When such deeper analysis is eventually undertaken it would be well to keep in mind that I might split again into a number of personality and dynamic factors (e.g., super ego strength, emotional stability) affecting the investment of fluid intelligence in crystallized intelligence skills (1963, p. 10).

Cattell presents the most comprehensive treatment of Investment Theory in two books completed during the latter portion of his career. The first, *Abilities: Their structure, growth and action*, was published in 1971. This was followed by a 1987 revision, *Intelligence: Its structure, growth and action* (see Section 5, pp. 138-146). A simplified model of Cattell's Investment Theory is presented in Figure 6.
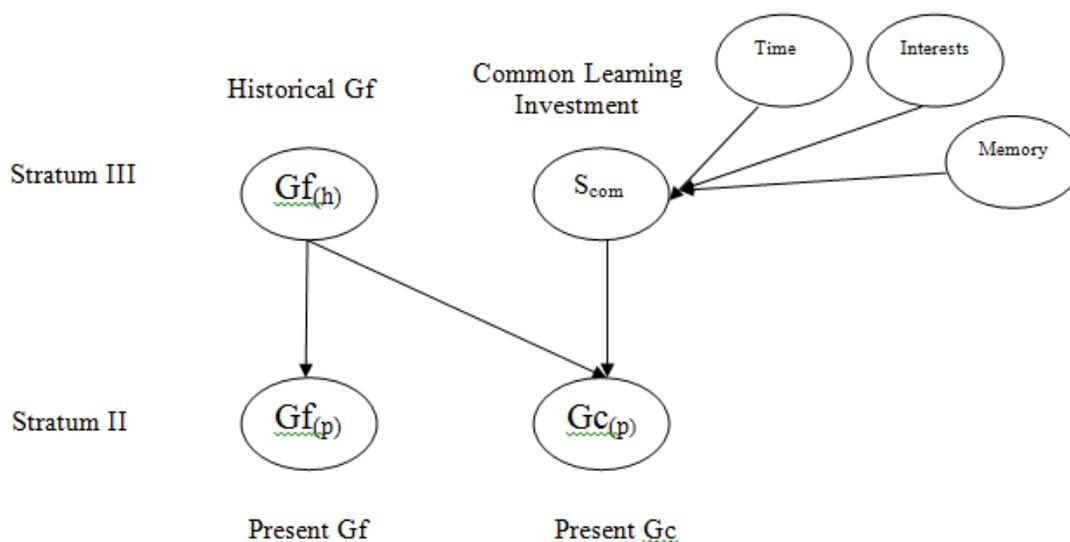
Figure 6. Cattell's Investment Model

Source: Adapted from Cattell (1987, Figure 6.3, p. 146)

Consistent with his previous discussions, Cattell defines Gf as "a single, general, relation-perceiving ability connected with the total, associational, neuron development of the cortex" (Cattell, 1987, p. 138). The term *fluid* is meant to imply that this type of intelligence "is not tied to any specific habits or sensory, motor, or memory area" (Cattell, 1987, p. 138). An important feature of this model is that two types of fluid ability are included, historical Gf and present day Gf. If at the present time an individual is administered a fluid intelligence assessment, such as the Raven's Progressive Matrices or Culture Fair Intelligence Test, the resulting score would indicate that individual's present day fluid intelligence. In contrast, historical Gf refers to fluid ability measured at some point in the past.

Cattell (1987, p. 139) defines Gc as "complex, acquired abilities, in the form of high-level judgmental skills in particular perceptual and motor areas." The term crystallized is meant to imply that "their expression is tied to a series of particular areas" (Cattell, 1987, p. 139) or that they have become frozen "in a specific shape of what was once fluid ability" (Cattell, 1987, p. 140). If an individual is administered a crystallized intelligence assessment, such as the Mill Hill Vocabulary scales or a general knowledge test, the resulting score reflects the individual's current crystallized intelligence (Cattell implies this is present day crystallized knowledge, though he does not explicitly use this terminology). As shown in the model, Gc is a function of *historical* Gf and Common Learning Investment (a gestalt of time, interest, and memory). That is, "this year's crystallized ability level is a function of last year's fluid ability level – and last year's interest in school work and abstract problems generally" (Cattell, 1987, p. 139). Although individuals choose where to invest their Gf, Cattell argues that a person who

demonstrates high ability in one crystallized ability area is likely to also be high in other areas. Thus, crystallized abilities will tend to exhibit a positive manifold.

To summarize, Investment Theory "says that g_c arises and has its particular form as a result of investing a general capacity, $g_{f(h)}$, in suitable learning experiences" (Cattell, 1987, p. 146). Although the theory is rather straightforward, Cattell and Horn (1978) acknowledge that it has been rather difficult to test empirically. Nevertheless, a small number of scholars have sought to do so. Not surprisingly, the results of these studies have been mixed, and in most cases less than conclusive.

Schmidt and Crano (1974) used cross-lagged panel analysis (Campbell, 1963; Pelz & Andrews, 1964) to test Investment Theory in two large samples of Milwaukee elementary school students. Fluid and crystallized intelligence were each assessed in Grade 4 and Grade 6, and the cross-lagged correlations were compared. Schmidt and Crano found support for Investment Theory in the sample of middle-socioeconomic students. That is, they found that the correlations between Gf measured in Grade 4 and Gc measured in Grade 6 were greater than the correlations between Gc measured in Grade 4 and Gf measured in Grade 6. However, they were surprised to find the opposite pattern of results among students who were from low-socioeconomic status backgrounds. Although Schmidt and Crano's study represents an important initial effort to empirically examine Investment Theory, the cross-lagged panel analysis method they employed was subsequently shown to be flawed. Rogosa (1980, p. 245) demonstrated that "cross-lagged correlation is not a useful procedure for the analysis of longitudinal panel data. In particular, the difference between the cross-lagged correlations is not a sound basis for causal inference." According to Rogosa (1980, p. 250), cross-lagged methodology is

based upon a number of "very restrictive" assumptions that are often ignored. These include stationarity (the assumption that causal structures are stable over time), synchronicity (measures within each wave are collected at the same time), and homogenous stability (see Kenny, 1975). Further, cross-lagged correlation has very low power and requires large sample sizes. Because of these large samples, very minor differences in correlations result in the null hypothesis being rejected (Rogosa, 1980, p. 257). Taken together, Rogosa (1980, p. 257) argues that "no justification was found for the use of CLC. In CLC both determinations of spuriousness and causal predominance are unsound." Given the problems with cross-lagged analysis, the generalizability of Schmidt and Crano's findings is somewhat limited.

Schweizer and Koch (2001) revisited Investment Theory by proposing a revision to Cattell's model. These authors propose that "learning mediates the influence of fluid intelligence on crystallized intelligence" (p. 66). Specifically, they argue that fluid intelligence impacts learning, which in turn "controls the transfer of knowledge to permanent memory" (p. 66). Thus, it is through learning that crystallized knowledge is created. Although Schweizer and Koch present this idea as novel, the basic premise is inherent in Cattell's (1987) presentation of Investment Theory. The authors tested this hypothesis in two small subsamples of German students. One subsample consisted of students aged 19-23 years ($n = 51$), the other subsample consisted of students aged 24-30 ($n = 53$). Learning, as measured by associative and complex learning tasks, was found to mediate the relationship between Gf and Gc in the younger subsample but not in the older subsample. The authors maintain that their results offer support for Cattell's contention that "professional specialization impairs the observability of the relationship between

fluid and crystallized intelligence" (p. 57). Indeed, Cattell (1987) does argue that one of the challenges of measuring crystallized intelligence is that as individuals grow older and leave school, they invest their Gf in increasingly specialized areas. As a result, assessing Gc becomes increasingly difficult with age as most crystallized assessments have tended to focus on the common body of knowledge learned in school rather than domain-specific knowledge acquired throughout adulthood (c.f. Ackerman, 2000; Horn & Blankson, 2005).

Kvist and Gustafsson (2008) set out to examine one prediction based on Investment Theory, specifically the idea that Gf and *g* would be equal in samples where individuals had equal opportunity to learn knowledge and skills. The authors proposed this would not be the case when individuals were heterogeneous with regard to opportunity to learn. They tested this idea by examining the factor structure of intelligence in an overall sample of Swedish workers, as well as subsamples of immigrant and non-immigrant populations. Kvist and Gustafsson found support for their proposition. The relationship of Gf and *g* was found to be .83 in the overall heterogenous sample while the relationship between Gf and *g* was found to be unity in each of the homogenous subsamples. However, the data these researchers examined was cross-sectional in nature. Accordingly, although the data permitted an examination of the general factor structure of intelligence using the Gf-Gc framework, it did not permit an examination of the central thesis of Investment Theory, that Gf and Gc are causally related.

Investment theory was most recently examined by Rindermann, Flores-Mendoza, and Mansur-Alves (2010). These researchers analyzed cross-lagged effects to investigate

the reciprocal effects of Gf and Gc in samples from Brazil and Germany. Results of the study were mixed. Contrary to Investment Theory, they found that fluid intelligence influenced crystallized intelligence and vice-versa. In partial support of Investment Theory, they found that parental education and socioeconomic status had a slightly stronger effect on Gc than Gf. However, despite statements by authors to the contrary, the methodology employed in the study was problematic in that the cross-lagged path analyses conducted by the authors appear to suffer from many of the same limitations of cross-lagged correlation analysis (e.g., Rogosa, 1980). This limits the generalizability of their results.

In sum, several well-intentioned attempts have been made to empirically test components of Cattell's (1971/1987) Investment Theory. However, results from each of these studies have been mixed at best. In many cases results are unclear or uninterpretable due to the limitations imposed by sample size and analytic strategy. As a result, Investment Theory remains primarily a theoretical contention rather than a robust, empirically supported phenomenon.

<u>PPIK</u>

Cattell's Investment Model is largely similar to Ackerman's (1996) PPIK Theory. PPIK represents Ackerman's integrative attempt to explain how adult intelligence develops. According to Ackerman (p. 227), "the PPIK theory of adult intellectual development integrates intelligence-as-process, personality, interests, and intelligence-as-knowledge." Like Cattell, Ackerman acknowledges that development of intelligence is dependent to some extent upon interests or motivation. However, Ackerman maintains that PPIK differs from Investment Theory by focusing not on Gf and Gc, but rather on

process and knowledge as two broad factors of intelligence. According to Ackerman, "intelligence-as-process" results in the development of Gf-type abilities. On the other hand, intelligence-as-knowledge results in the development of Gc-type abilities (see Ackerman, 1996, Figure 3, p. 238). Ackerman's PPIK model also places more attention on domain-specific knowledge (such as specific legal knowledge for lawyers, or medical knowledge for physicians). Ackerman (2000) has referred to domain-specific knowledge as the "dark matter" of adult intelligence, and he acknowledges it is very difficult to measure given its unique nature. In contrast, Cattell's concept of Gc appears to be wider in scope. Accordingly, Gc has typically come to refer to broad, culturally acquired knowledge rather than job- or domain-specific knowledge. However, it should be acknowledged that the latter idea of domain-specific knowledge would be considered a special case of the more broadly conceived construct of Gc. In this way, all domain-specific knowledge would be considered crystallized, but not all crystallized knowledge is domain-specific. The current study is concerned with Gc as it refers to broad, acculturated learning rather than development or demonstration of domain-specific knowledge.

<div align="center">Carroll's (1993) Human Cognitive Abilities</div>

By the latter half of the twentieth century, researchers had conducted hundreds of empirical studies examining the structure of intelligence. This body of evidence was vast and often confusing. Amidst this backdrop, educational psychologist John Carroll increasingly "sensed the field's need for a thoroughgoing survey and critique of the voluminous results in the factor-analytic literature on cognitive ability" (Carroll, 1993, p. vii). To address this need, Carroll began collecting and systematically evaluating empirical studies of cognitive ability. Some twelve years after he had begun, Carroll had

managed to gather and factor-analyze over 461 unique data sets. He subsequently

synthesized these findings to construct a three-stratum model of cognitive abilities. His

efforts culminated in 1993 with the publication of his seminal book *Human Cognitive*

Abilities. The book has been very highly regarded (e.g., Burns, 1994; Eysenck, 1994,

Jensen, 2004). For example, McGrew (2009, p. 2) has argued that *Human Cognitive*

Abilities

> represents to the field of applied psychometrics a work similar in
> stature to other *principia* publications in other scientific fields
> (e.g., Newton's three volume, *The Mathematical Principles of*
> *Natural Philosophy*, or *Principia* as it became known and
> Whitehead & Russell's, *Principia Mathematica*).

The near universal high acclaim and subsequent impact of Carroll's (1993) work

can likely be attributed to several factors. The first of these is scope. Lubinski (2000, p.

412) claims that Carroll's three-stratum model is "in many respects, not new. Embryonic

outlines are seen in earlier psychometric work (Burt, Cattell, Guttman, Humphreys, and

Vernon, among others)." Rather, according to Lubinski, the importance of Carroll's

(1993) contribution stems from the "unparalleled" bases of evidence upon which his

model is built.

Using the results of his many analyses, Carroll (1993) ultimately constructed a

three-stratum model (presented in Figure 6) that is in many ways analogous to the Gf-Gc

theory advanced by Cattell and Horn. A model representing Cattell and Horn's Gf-Gc

theory was presented earlier in Figure 5. Within both models, Gf and Gc are conceived

as unique, broad (stratum II) abilities that lie alongside other broad abilities such as short

term memory and processing speed. These broad abilities can be measured by a number

of narrow (stratum I) abilities. In the case of fluid intelligence, these narrow stratum I

abilities would include performance on matrices tests and Gf-loaded verbal analogies.

Carroll does not disguise this fact, and in *Human Cognitive Abilities* (1993, p. 62) he acknowledges that the Cattell-Horn model "appears to offer the most well-founded and reasonable approach to an acceptable theory of the structure of cognitive abilities." As McGrew (2005) and Alfonso et al. (2005) have shown, when the models are compared side-by-side, the stratum II ability factors are much the same with the exception of some minor differences in terminology. Likewise, both the Carroll and Cattell-Horn models acknowledge that these broad, stratum II abilities cause multiple narrow abilities which constitute the lowest level (stratum I) of both models. As Kvist and Gustafsson (2008, p. 422) note, these narrow abilities largely "correspond to factors previously identified by Thurstone (1938), Guilford (1967) and other researchers working in the tradition of multiple factor analysis." The primary difference between Carroll's model and the Cattell-Horn Gf − Gc model is that Carroll argues for the existence of a general factor (or *g*-factor) at stratum III, superordinate over the broad stratum II abilities. The existence and nature of this general factor has aroused considerable discussion among intelligence researchers. This is described in the section which follows.

<u>The *g*-factor and Gf −Gc Theory</u>

Carroll (1993) is not alone in his belief that both theory and empirical evidence suggest the presence of a general factor. Following Spearman (1904, 1927), a number of researchers advocate the existence of a *g*-factor, including Jensen (1998), Gottfredsen (1997), Schmidt and Hunter (e.g., Hunter, 1986; Schmidt, 2002; Schmidt and Hunter, 1992, 1998, 2004), Ree and Earles (1991), and Gustafsson and colleagues (Gustafsson, 1988; Kvist & Gustafsson). Nevertheless, there is continuing debate regarding what the g-factor represents (Kvist & Gustafsson, 2008).

In the current study, the general factor *g* or GCA is considered a latent variable that causes the correlations between different measures of cognitive ability. That is, *g* refers to the shared variance between cognitive ability measures, or rather what different measures of ability share in common. *g* emerges when a diverse set of abilities are measured. Most *g* theorists do not deny the existence of Gf and Gc; however, they maintain that Gf and Gc are merely different kinds of indicators of the higher-order latent variable *g* and not unique types or kinds of intelligence. The GCA model of intelligence is presented in Figure 8.

As shown in Figure 5, the Cattell-Horn model in its current form does not include a general factor. As Kvist and Gustafsson (2008, p. 423) note, this is largely due to the fact that "Horn (see, e.g., Horn & Blankson, 2005; Horn & Noll, 1997) has strongly objected to the idea of a general factor, favoring instead a hierarchical model with broad correlated factors at stratum II." Specifically, Horn argues that a *g*-factor at stratum III lacks "factorial invariance." That is, the *g*-factor is simply a statistical artifact that emerges from unique combinations of stratum II ability tests. Horn and Blankson (2005, p. 53) are particularly emphatic in their denial of a general factor:

> The structural evidence thus does not support a theory of *g*. The developmental evidence is even less supportive. In general, construct validation evidence is counter to a theory that human intelligence is organized in accordance with one common principle or influence. The evidence from several sources points in the direction of several distinct kinds of factors.

However, Cattell himself was more sympathetic to the idea of a general factor at stratum III. For example, Cattell (1963) maintained that the positive correlations among broad abilities should not be interpreted as

Stratum III
General Ability

g

Gf	Fluid Intelligence
Gc	Crystallized Intelligence
Gy	General memory and learning
Gv	Broad visual perception
Gu	Broad auditory perception
Gr	Broad retrieval ability
Gs	Broad cognitive speediness
Gt	Decision/reaction time/speed

Stratum II
Broad Abilities

Stratum I - Narrow Abilities
(Not Shown)
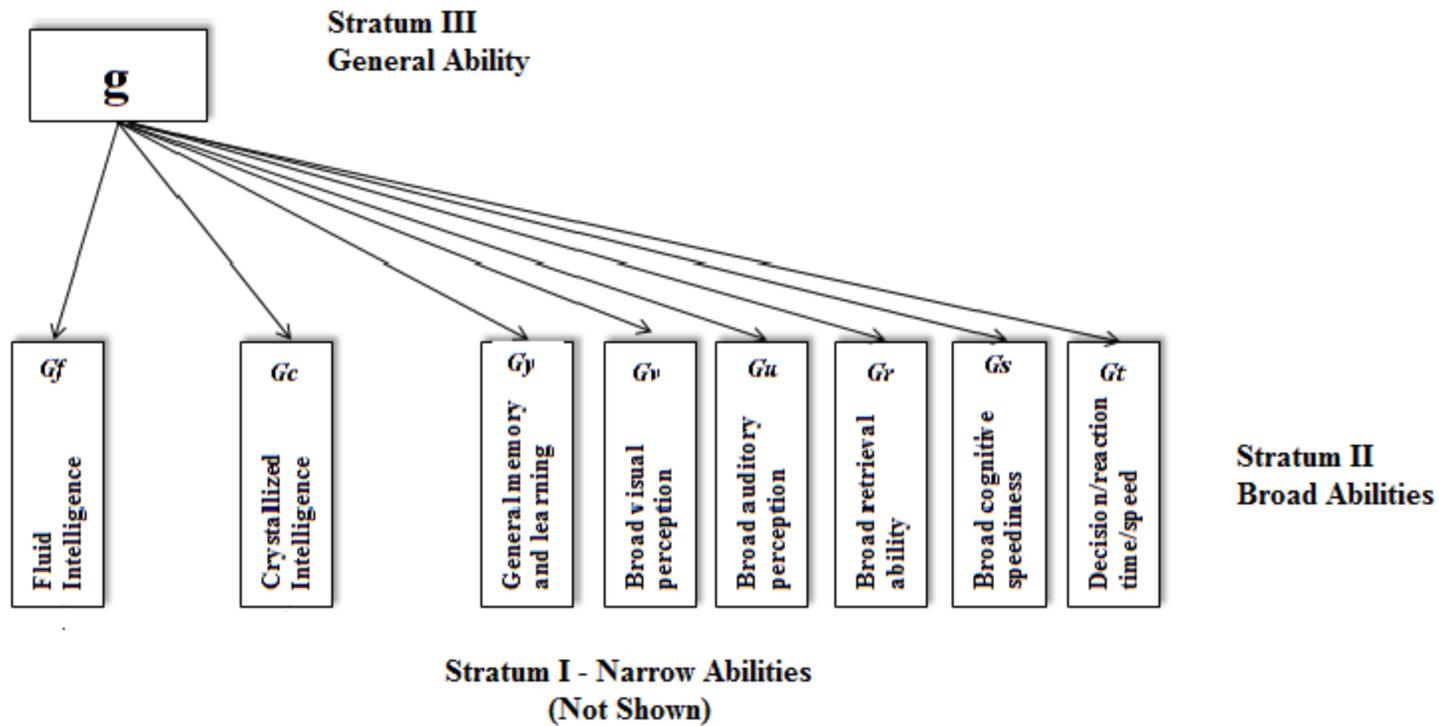
Figure 7. Carroll's Three-stratum Model of Intelligence

Source: Adapted from: Flanagan et al. (2002) and Alfonso et al. (2005, p. 187, Figure 9.1)
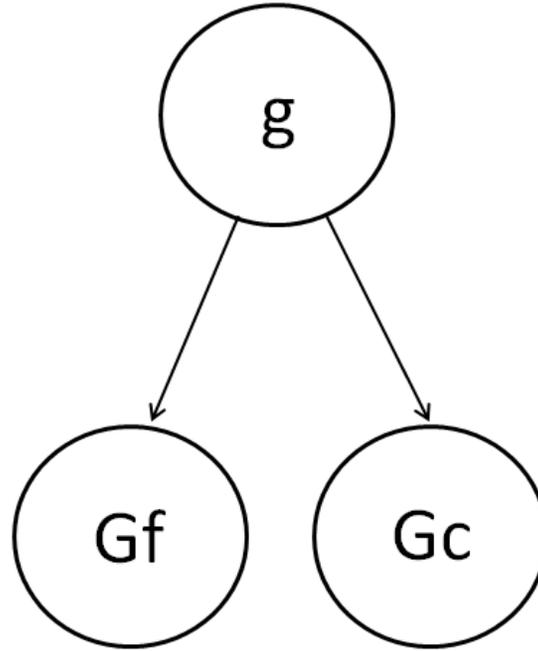
Figure 8. GCA Model of Intelligence

> "fluid and crystallized ability form a single third-order factor," but rather that a single influence, which is fluid ability as it stood during the formative period of crystallized ability, is causative to the present levels of both. (p. 15).

Thus, Cattell viewed the *g*-factor as synonymous with *historical* fluid ability. This is shown in the investment model of Figure 6, whereby historical Gf (stratum III) is proposed as the cause of present-day Gf and Gc (stratum II).

Consistent with this line of reasoning, some researchers such as Undheim (1981a, 1981b) and Gustafsson (1984) have argued that "the characteristics of the *g*-factor as described by Spearman (1904, 1927) agree so well with the characteristics of the *Gf*-factor as described by Horn and Cattell (1966), that *g* and *Gf* should be considered to be one and the same factor" (Kvist & Gustafsson, 2008, p. 423). In support of this idea, several scholars (Gustafsson, 1984, 1988, 1994, 2002; Keith, 2005; Reynolds & Keith, 2007; Undheim, 1981a, 1981b; Undheim & Gustafsson, 1987) have presented evidence suggesting that Gf is perfectly related, or equivalent, to *g*.

However, other researchers have disagreed with the assertion that *g* and Gf are equivalent constructs (e.g., Blair, 2006; Carroll, 1993; Gignac, 2006; Robinson, 1999). For example, Gignac (2006) examined correlation matrices from several major test batteries using the single trait-correlated uniqueness (STCU) CFA method. He found that verbal intelligence subtests, especially crystallized subtests, were strongly correlated with a general factor, thereby providing evidence that Gc measures are "the best indicators of '*g*'" (Gignac, 2006, p. 29). However, some researchers (e.g., Ashton & Lee, 2006; Kvist & Gustafsson, 2008) have questioned Gignac's conclusions based on the analytic approach he employed.

Gf and Gc: An Alternate Interpretation

In contrast to the Cattell-Horn Gf –Gc theory, Lohman (1993, p. 13) proposes that problems or tests measuring fluid and crystallized abilities can be viewed as lying along a continuum (Figure 9). The horizontal line in his model represents both the novelty of the problem (familiar vs. novel) as well as the degree of transfer required (near transfer vs. far transfer). Lohman argues that his use of the term transfer is consistent with Gagne's (1970) idea of *lateral transfer*. As such, it refers to "how broadly the individual can generalize what he has learned to a new situation" (Gagne, 1970, p. 336). Tests or problems requiring only rote memory would lie to the far left of the continuum. Accordingly, "as one moves to the right on this scale, problems become increasingly novel and thus require increasing transfer" (Lohman, 1993, p. 13). Lohman maintains that he is far from unique in suggesting that cognitive abilities can be conceptualized in such a manner, with similar models (some of which predate Gf-Gc theory) having previously been presented by a number of scholars including Stern (1914), Anastasi (1937), Cronbach (1970), Elshout (1983), Raaheim (1984), and Sternberg (1985).

As an illustration of this model, Figure 10 presents a sample transfer continuum for multiplication problems (adapted from Lohman, 1993, p. 14). The example problem on the far left (2 x 8) assumes a student learns multiplication when numbers are presented in a horizontal format (e.g., duplication or rote memory). Changing the position of the numbers to a vertical format requires some degree of transfer, which in turn increases when a multiplication problem is presented using words or stories. As illustrated on the far right, further transfer would be needed to solve a multiplication problem presented in a novel or abstract form, such as a Raven's Matrix.

	Gc Crystallized Abilities (Achievement)	Gf Fluid Abilities (Aptitude)	
Near Transfer	↓	↓	**Far Transfer**

Familiar Tasks   **Novel Tasks**
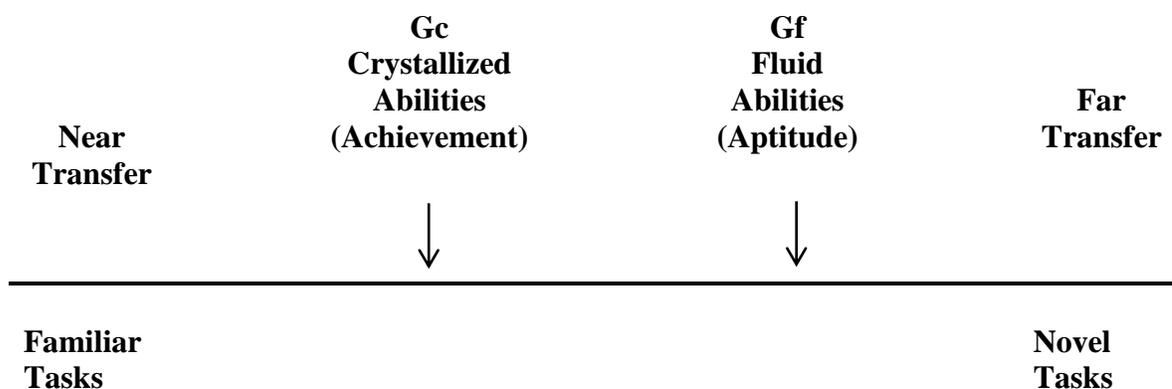
Figure 9. Lohman's (1993) Novelty-Transfer Continuum

Source: Adapted from Lohman (1993, Figure 1, p. 13)

Near Transfer		The local cinema charges $7 per ticket. Sue needs 4 tickets, how much will…	**Far Transfer**
2 x 8 = ?	6 x 3		(matrix problem)
Identical Format	*Similar Format*	*Word Problem*	*Matrix Problem*

Familiar Tasks   **Novel Tasks**
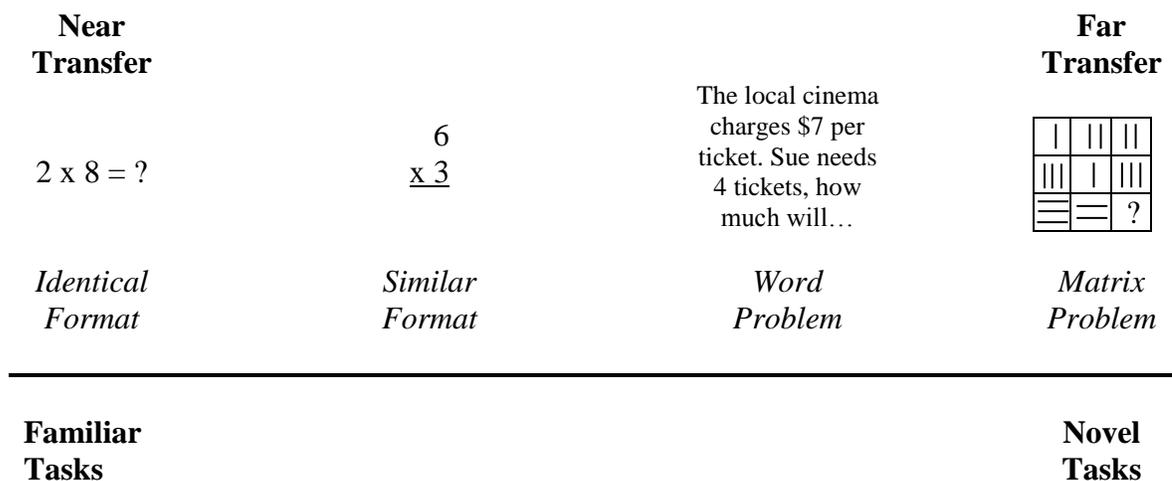
Figure 10. A Transfer Continuum for Multiplication Problems

Source: Adapted from Lohman (1993, Figure 2, p. 14)

Lohman (1993, p. 13) maintains that placing fluid and crystallized abilities "on the same line implies that these are best seen as two aspects of the same thing rather than qualitatively different things." Snow (1980) also appears to adhere to this line of reasoning:

> …[Crystallized ability] represents the long-term accumulation of knowledge and skills, organized into functional cognitive systems by prior learning, that are…units for use in future learning… Thus [Gc] may represent prior assemblies of performance processes retrieved as a system and applied anew in instructional or other…situations not unlike those experienced in the past, while [fluid ability] may represent new assemblies of performance processes needed for more extreme adaptations to novel situations….Both functions develop through exercise, and perhaps both can be understood as variations on a central production system development (p. 37)

Such reasoning lies in contrast to Cattell and Horn who clearly view Gf and Gc as independent, albeit related, constructs.

The Stability of Gf and Gc

Within-person Stability of
Cognitive Ability Scores over Time

A number of studies conducted over the past half-century have demonstrated that individual differences in cognitive ability remain quite stable over time (Conley, 1984; Deary, 2000, 2001). As Deary and colleagues (Deary; 2000; Deary, Whalley, Lemon, Crawford, & Starr, 2000, p. 50) note, researchers have examined the stability of cognitive ability scores using different time frames including within childhood (e.g., Humphreys, 1989), within adulthood/old age (e.g., Mortensen & Kleven, 1993; Nisbet, 1957; Owens, 1966; Schwartzman, Gold, Andres, Arbuckle, & Chaikelson, 1987), and between

childhood and adulthood/old age (e.g., Deary et al., 2000; Kangas & Bradway, 1971).

Table 2 presents a summary of key studies which have examined this stability.

Deary et al.'s (2000) study is of particular interest as it examined the stability of IQ over an especially long interval. In 1932, all Scottish children born in 1921 took the Moray House Test, a validated measure of intelligence, as part of the Scottish Mental Survey. In 1998, Deary and colleagues administered the Moray House Test to 101 individuals who participated in the Scottish Mental Survey some 66 years earlier. 97 of these individuals, now aged 77, also completed Raven's Progressive Matrices. Deary et al. found that IQ measured with the Moray House Test at age 11 correlated .63 with IQ measured with the Moray House Test at age 77 (95% CI = .50 - .74). This raw correlation increases to .73 when corrected for range restriction, and the authors acknowledge that the correlation would be even larger if a correction for attenuation due to measurement error were made. In addition, the 1932 Moray House Test correlated .48 with the 1998 Raven's Progressive Matrices scores, a magnitude similar to the .57 correlation observed between the Moray House and Raven's tests administered in 1998.

Although cognitive ability scores do appear to be relatively stable over time, there is a general pattern whereby scores within persons appear to be considerably more stable over shorter time periods (more proximal) vs. longer (more distal) time periods. Research on Gf, Gc, and age offers some illumination into this phenomenon.

Cognitive Ability and Age

Corno et al. (2002) maintain that although Cattell's initial (1940) distinction between fluid and crystallized intelligence attracted some attention shortly after its release, it was not until the 1960's that the distinction between Gf and Gc became

Table 2. Stability of General Cognitive Ability Scores Over Time

Study	Interval (Years)	Mean Age (Initial Test)	Mean Age (Retest)	N	Test	Test-retest r (Observed)
Deary et al. (2000)	66	11	77	101	Moray House Test	.63
Dauphinais & Bradley (1979)	49	13	62	80	Stanford-Binet/WAIS	.62
Owens (1966)	42	19	61	96	Army Alpha	.78
	31	19	50	96	Army Alpha	.79
	11	50	61	96	Army Alpha	.92
Schwartzman et al. (1987)	40	25	65	260	Revised Examination "M"	.78
Kangas & Bradway (1971)	38	4	42	48	Stanford-Binet	.41
	28	14	42	48	Stanford-Binet	.68
	13	29	42	48	WAIS	.73
Nisbet (1957)	24	22	47	141	Simplex Group Test	.48
Honzik & Macfarlane (1973)	22	18	40	110	Weschler-Bellevue/WAIS	.74
Mortensen & Kleven (1993)	20	50	70	141	WAIS	.90
	10	50	60	141	WAIS	.94
	10	60	70	141	WAIS	.91
Tuddenham et al. (1968)	13	30	43	164	AGCT	.64-.79
Dodrill (1983)	5	33	38	30	Wonderlic	.94
	5	33	38	30	WAIS	.96

prominent. Corno et al. argue that this newfound prominence can largely be attributed to research by Horn and Cattell (e.g., Horn & Cattell, 1966; Horn & Cattell, 1967) that showed Gf and Gc demonstrate differential relationships with age.

Using data from a sample of 297 adults, Horn and Cattell (1966) observed a general pattern whereby Gf abilities correlated negatively with age while Gc abilities correlated positively with age. Horn and Cattell (1967) used the same sample to examine this ability-age phenomenon in more detail. Horn and Cattell (1967, p. 124) noted that much of the earlier research on age and intelligence appeared contradictory: "Several studies have shown that intelligence declines with age in adulthood, others have shown that it increases, and still others have shown that it remains more or less constant." Horn and Cattell argued that these different findings could be explained by the fact that earlier studies measured Gf and Gc to differing degrees.   A large volume of subsequent research has utilized the Gf – Gc framework to examine the relationship between age and intelligence.   As shown in the discussion which follows, findings have largely been consistent with Horn and Cattell's (1966, 1967) initial observations. On average, Performance IQ scores (largely analogous to Gf) have been found to decline substantially with age while scores on verbal measures (largely analogous to Gc) have been found to remain relatively stable (Wang & Kaufman, 1993). Botwinick (1977) has referred to this as the "classic intellectual aging pattern" (although Wang and Kaufman point out that he attributed the phenomenon to speeded vs. non-speeded tasks rather than the Gf – Gc dichotomy).

<u>Gf and Age</u>

On average, Gf has been found to increase throughout young adulthood, peaking between ages 26 and 35, after which time it begins a period of steady, continuing decline (Kaufman, Johnson, & Liu, 2008; Wang & Kaufman, 1993). Horn and Blankson (2005, p. 48-49) note that decline in fluid ability has been observed in multiple types of Gf test measures including syllogisms and concept formation (e.g., McGrew, Werder, & Woodcock, 1991), metaphors and analogies (e.g., Salthouse, Kausler, & Saults, 1990), number, letter, and figure series (e.g., Babcock, 1994; Noll & Horn, 1998; Salthouse et al., 1990), and mental rotation and matrices (e.g., Babcock, 1994; Cattell, 1979). The relationship between age and performance on the Raven's Advanced Progressive Matrices (RAPM) is particularly illustrative of this pattern of decline. For example Babcock (1994) administered the RAPM to 183 adults between the ages of 21 and 83. She found that age correlated -.46 with RAPM performance. Age-related declines in Gf have largely been attributed to decrements in working memory, processing speed, and rule application (Babcock, 1994; Salthouse, 1991).   Given that Gf demonstrates substantial decline throughout much of adult age range, Horn and colleagues (Horn, 1991; Horn & Blankson, 2005) have referred to it as a *vulnerable* ability (Horn & Blankson, 2005). Working memory (Gsm/SAR) and processing speed (Gs) are also classified as vulnerable abilities.

Gc and Age

In contrast to fluid ability, crystallized ability has been found to increase with age throughout most of adulthood (e.g., Harwood & Naylor, 1971; Horn, 1998; Horn & Cattell, 1967; Horn & Hofer, 1992; Kaufman et al., 2008; Rabbitt & Abson, 1991; Schaie, 1996; Stankov, 1988; Stankov & Horn, 1980; Wang & Kaufman, 1993). Gc has been estimated to increase until approximately age 70 (Schaie, 1996), after which it may decrease slightly. However, some studies (e.g., Harwood & Naylor, 1971) have found that Gc may continue to increase even into the 80s. Along these same lines, compared with young adults, middle-aged adults have been found to score significantly higher on assessments of domain-specific knowledge (Ackerman, 2000). Given that Gc demonstrates little or no decline throughout much of the age range, Horn and colleagues (Horn, 1991; Horn & Blankson, 2005) have referred to it as a *maintained* ability. Evidence also suggests that long-term memory (Glm/TSR) and reading/writing (Grw) are also maintained abilities (Horn & Blankson, 2005; Kaufman et al., 2008). A summary of the age differences in broad abilities during adulthood is presented in Figure 11 (from Horn, 1986, p. 52, Figure 2.3).

Improving Scores on Measures of Fluid Intelligence

Given that fluid intelligence is known to decline throughout adulthood, there has been increasing interest in the extent to which this decline can be retarded or reversed. Training interventions have been advanced as one such mechanism by which this might occur. Two recent studies have examined the extent to which fluid intelligence scores can
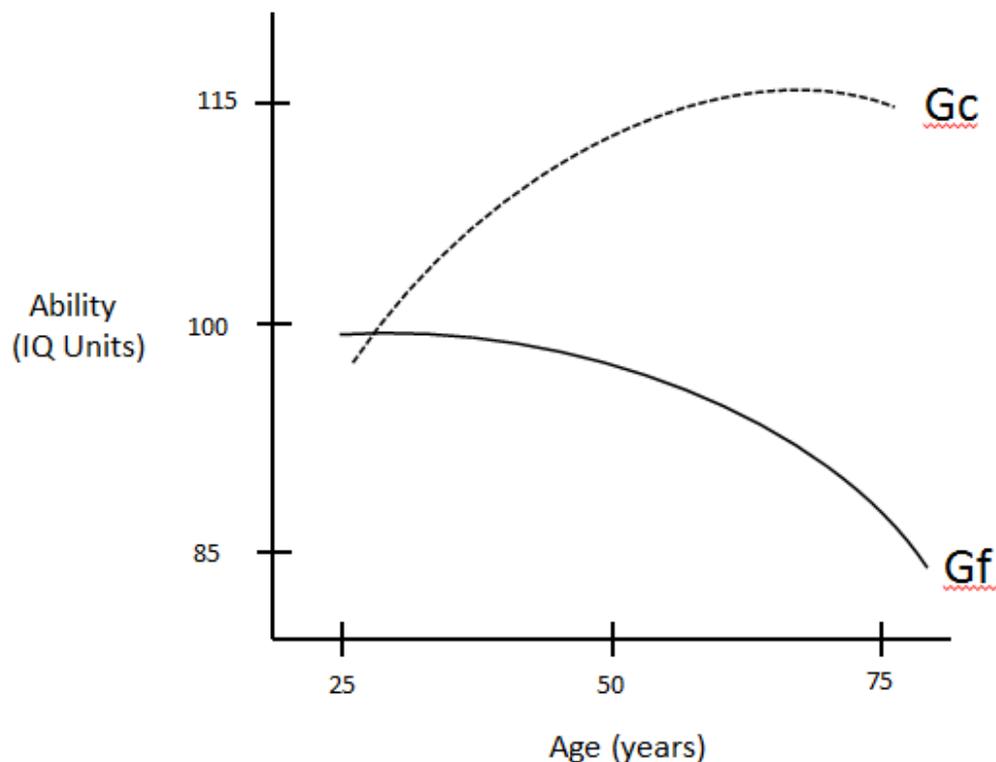
Figure 11. Age Differences in Broad Abilities During Adulthood

Source: Adapted fron Horn (1986, p. 52, Figure 2.3)

be increased through training. Basak, Boot, Voss, and Kramer (2008) examined this issue in a sample of 19 older adults (mean age = 70.05, *SD* 4.94). Participants participated in 23.5 hours of training in a real-time strategy video game, *Rise of Nations*. When compared to a control group of 19 individuals who did not receive training, trainees displayed score increases (from 44% of items correct pre-training to 59% of items correct post-training) on an abbreviated measure of the Raven's Advanced Progressive Matrices. No increases in Gf were observed for individuals assigned to the control group.

In a similar study, Jaeggi, Buschkuehl, Jonides, and Perrig (2008) investigated the effect of working memory training on fluid intelligence scores. Participants were young adults (mean age 25.6, *SD* 3.3) who completed between 8 and 19 days of training on a demanding working memory task (a computer-administered dual *n*-back task; Jaeggi et al., 2007). Compared with individuals assigned to matched control groups, trainees displayed greater increases on a shortened measure of fluid intelligence (either the Ravens' Advanced Progressive Matrices or the Bochumer-Matrizen Test). Jaeggi et al. (2008, p. 6831) propose that this training-related gain in Gf "emerges because of the inherent properties of the training task." That is, the working memory task may have engaged executive processes and increased participants' ability to control attention.

Recent research by Bors and Vigneau (2003) has shown that tests of fluid ability are subject to substantial practice effects. These researchers administered the Raven's Advanced Progressive Matrices to a sample of 67 individuals on three separate occasions. They found that subjects correctly answered an average of approximately two additional questions (out of 36 possible) with each subsequent administration of the test. Further, fewer questions were left unanswered during later test administrations. Bors and Vigneau (2003, p. 301) found that the individual RAPM item reliabilities were quite low, suggesting that "the improvements in performance were not based on the acquisition or on the retention of item-specific information, but rather on the development or refinement of some process or activity more general in nature." Thus, it appears individual performance on Gf tests may improve as persons become accustomed to what initially appears to be a novel question format. Greenfield (1998) has argued that global rises in nonverbal IQ (i.e., the Flynn effect; Flynn, 1987) in Western countries can be explained

by the fact that individuals have become increasingly exposed to communication technology in the form of TV, film, computers, and video games. She proposes that the iconic imagery and visual-spatial content of these modern communication modalities have resulted in fluid intelligence items, such as matrix reasoning problems, being viewed as less novel than in earlier times.

A recent study by Fox and Charness (2010) demonstrates that even simple variations in the way fluid ability tests are measured can impact the scores that are obtained. These researchers administered a shortened version of the Raven's Advanced Progressive Matrices and other cognitive tests to samples of older (mean age = 73) and younger (mean age = 19) adults. Compared with older adults who completed the tests in the typical manner, older adults who were instructed to think aloud while taking the test performed significantly better ($d = .73$ and $d = .92$) on the RAPM. According to the authors, this equates to a score gain of approximately 11 IQ points. Similar gains were not observed for tests other than the RAPM, nor were these effects found in the young adult sample. A limitation of the study was that the researchers did not examine within-person score improvements. Each participant completed the RAPM only once (under either the standard or talk aloud condition), and conclusions were drawn based on standardized differences of the randomly assigned group means. Further, as is typical in experimental research, sample sizes were quite small thereby increasing the possibility that the results obtained were due to sampling error.

The results of these studies suggest that scores on fluid ability tests are malleable to some degree. However, there has yet to be research establishing whether gains in Gf are long-lasting rather than temporary. More importantly, research has not yet

established whether any of the observed gains in Gf demonstrate appreciable relationships with real-world outcomes, such as increases in daily functioning, learning, or job performance. Given that Gf is posited to have a biological basis, it is unlikely that training, practice, or administration manipulations would meaningfully impact the underlying trait. Consistent with this line of reasoning, a recent meta-analysis by te Nijenhuis, van Vianen, & van der Flier (2007) suggests score gains on cognitive tests are not related to *g*.

What are the implications of these findings for Gf – Gc theory? The theory includes both the theoretical notion of Gf and the proposition that certain types of tests or items (e.g., the Raven's) measure Gf. The theory postulates that Gf is basic and is not dependent on learning, while Gc and its measures directly reflect past learning. At minimum, these findings show that Gf measures have a problem: they should not be affected by learning and practice but they are. This seems to make it impossible to measure Gf independent of past learning and practice.

CHAPTER 3

HYPOTHESIS DEVELOPMENT

<u>Chapter Overview</u>

In this chapter I consider the criterion-related validity of fluid and crystallized ability in the context of research on past performance, the nature of work, and expert performance. I conclude the chapter by arguing that compared to measures of fluid ability, crystallized ability measures should more strongly predict real-world criteria such as academic, training, and job performance. In developing my hypotheses, I adopt the perspective of General Mental Ability Theory. That is, I conceptualize Gf and Gc not as unique types of intelligence, but rather as indicators of the higher-order construct of *g*.

<u>The Criterion-related Validity of</u>
<u>Fluid and Crystallized Ability</u>

Thus far, the vast majority of the discussion regarding the relative importance of Gf and Gc has been structural in nature. That is, researchers have largely focused on the results of exploratory and confirmatory factor analyses. As discussed earlier, a large body of research has also focused on the relative stability of fluid and crystallized abilities during adulthood. Although these areas of inquiry can indeed be informative, structural evidence and age-related evidence alone do not present a complete picture of the relative importance of Gf and Gc, nor do they address the actual usefulness of these constructs for predicting performance in the real world. The current study adopts a different approach by focusing on the criterion-related validity of ability constructs within the Cattell-Horn-Carroll (CHC) framework. Specifically, I will examine the

extent to which Gf and Gc are related to real-world outcomes including academic performance, training performance, and job performance. Because Gf and Gc are conceptualized as independent, albeit related, constructs, they are expected to relate differently to external measures of performance (Horn & Blankson, 2005). That is, Gf and Gc should display different criterion-related validities.

A number of earlier meta-analyses and quantitative reviews have examined the relationship between cognitive ability and academic performance (e.g., Kuncel & Hezlett, 2007; Kuncel, Hezlett, & Ones, 2001, 2004; Sackett, Borneman, & Connelly, 2008), vocational training performance (e.g., Ghiselli, 1966; Ree & Earles, 1991; Schmidt & Hunter, 1998), and job performance (e.g., Ghiselli, 1966; Hunter, 1986; Hunter & Hunter, 1984; Salgado et al., 2003a; Schmidt & Hunter, 1998). These studies have found that cognitive ability is one of the best predictors of real-world performance. However, no previous meta-analyses have examined the ability – performance relationship using the CHC framework. Thus, the summary evidence of the relative validity of Gf and Gc has been extremely sparse and anecdotal in nature (e.g., Jensen, 1998).

Further, although there are several exceptions, theorists have been generally silent with regard to the issue of criterion-related validity. Since fluid intelligence has played a central role in theoretical and structural models of intelligence, one might assume that Gf measures will be expected to predict real-world performance to a greater extent than Gc measures. Indeed, a number of researchers have operationalized cognitive ability using only Gf measures (e.g., Côté & Miners, 2006; DiFabio & Busoni, 2007; DiFabio & Palazzechi, 2009). However, I argue that the opposite pattern of results is more likely to be the case. There are a number of reasons to expect that crystallized ability measures

will be the stronger predictors of performance. In outlining this argument I draw on research literatures that have examined past performance, the nature of work performance, the development of expertise, and the relationship between age and job performance.

<div align="center">Past Performance</div>

Fluid ability primarily reflects an ability to deal with novel information. In contrast, crystallized ability reflects the extent and efficiency with which one has learned in the past. As such, Gc measures serve as broad and robust indicators of *past performance*. One of the most established phenomena in psychology is that performance in the past is one of the best predictors of performance in the future (e.g., Locke, Frederick, Lee, & Bobko, 1984; Oullette & Wood, 1998; Triandis, 1977, 1980). For example, grades attained during high school are particularly good predictors of grades attained during college (Harris, 1940; Hezlett et al., 2001). Likewise, undergraduate GPA has been found to predict a number of desirable academic outcomes for graduate students including overall graduate GPA, first-year graduate GPA, comprehensive exam performance, faculty ratings of performance, degree attainment, and time to degree completion (Kuncel et al., 2001). More recent research has suggested that the quality of management scholars' early publications is strongly related to the quality of their later publications ($r = .62$; Bedeian, Cavazos, Hunt, & Jauch, 2010). According to GCA theory, past performance predicts future performance because both share the same cause: *g* or GCA.

An alternate, and more behavioristic, explanation for the relationship between past and future performance has been offered by Oullette and Wood (1998). They have shown that past behavior impacts future behavior through two primary processes, habit and intention:

> Well-practiced behaviors in constant contexts recur because the processing that initiates and controls their performance becomes automatic. Frequency of past behavior then reflects habit strength and has a direct effect on future performance. Alternately, when behaviors are not well learned or when they are performed in unstable or difficult contexts, conscious decision making is likely to be necessary to initiate and carry out the behavior. Under these conditions, past behavior (along with attitudes and subjective norms) may contribute to intentions, and behavior is guided by intentions. (p. 54)

Gc measures are efficient assessments of both the ability and non-ability (motivation, time, opportunity, memory) aspects of past performance. This is a key idea in Cattell's (1971/1987) Investment Model, whereby time, interests, and memory all contribute to Gc. At least this is true for narrow or specific measures. As I discuss later, this prediction of the theory may not hold for broad or generic measures of Gc. This idea also underlies Ackerman's (1996) PPIK Theory. Individuals scoring high on Gc assessments demonstrate that they not only have been *able* to learn material in the past, they were also *willing* to invest time and energy to some extent in doing so. As a result, when compared to Gf measures, Gc measures are expected to correlate more highly with real-world performance, which is also determined by both ability and effort.

<u>The Nature of Work</u>

The very nature of work suggests that Gc measures will demonstrate superior validity to Gf measures. Work performance is largely dependent on the mastery of a core

body of job knowledge, just as academic performance is largely dependent on the mastery of a core body of subject knowledge. After an initial period of learning, work becomes increasingly routine (Goldberg, 2005; Horn & Blankson, 2005). Although there are certainly fields where workers encounter novelty to a greater degree (e.g., theoretical physics, abstract mathematics, certain creative fields), these are the exception rather than the rule. Hunter, Schmidt, and colleagues (e.g., Hunter, 1983; Hunter, 1986; Schmidt, Hunter, & Outerbridge, 1986; Schmidt & Hunter, 1992; Schmidt & Hunter, 1993) have demonstrated that cognitive ability does not impact supervisory ratings of job performance directly, but rather does so indirectly through job knowledge:

> the major causal impact of mental ability was not on performance capability (work sample performance), but rather on the acquisition of job knowledge. What appears to happen is this: People with higher mental ability acquire more job knowledge, and job knowledge, in turn, is the major determinant of work sample performance. (Schmidt & Hunter, 1992, p. 90).

Job knowledge refers to the extent to which workers are familiar with the tasks, procedures, and other aspects necessary to successfully function in a particular job (Schmidt et al., 1986). Meta-analyses have shown that performance on job knowledge tests strongly correlates with job performance (ρ = .48; Schmidt & Hunter, 1998). Ree, Carretta, and Teachout (1995) have found support for a similar model whereby *g* impacts training performance through prior job knowledge as well as job knowledge gained during training. As noted earlier, within the CHC framework job knowledge would be considered a special case of crystallized ability (specific Gc). That is, it does not reflect abstract reasoning (Gf) ability, but rather reflects specific knowledge that has been gained through learning and experience.

Expert Performance

The growing literature on expertise development and expert performance also supports the idea that crystallized ability is especially important in determining real-world performance. Ericsson and Charness (1994, p. 731) define expert performance as "consistently superior performance on a set of representative tasks for the domain that can be administered to any subject." Research has shown that expertise takes extensive time to develop, at least 10 years in many cases (Ericsson & Charness, 1994; Ericsson & Lehmann, 1996). Given requisite levels of cognitive ability, expertise development is largely a function of the extent to which individuals have engaged in deliberate practice (Ericsson, Krampe, & Tesch-Römer, 1993). Expert performance has been empirically examined in a number of fields including chess (e.g., Charness, 1981; Chase & Simon, 1973; de Groot, 1946/1978), medicine (e.g., Norman, Coblentz, Brooks, & Babcock, 1992; Patel & Groen, 1991; Schmidt, Norman, & Boshuizen, 1990), accounting (e.g., Johnson, Jamal, & Berryman, 1991; Johnson, Grazioli, Jamal, & Zualkerman, 1992), and typewriting (Genter, 1988; Salthouse, 1986).

A wealth of research indicates that experts reason differently than novices (Ericsson & Charness, 1994; Ericsson & Lehmann, 1996; Horn & Blankson, 2005). Novices tend to approach problems inductively. That is, they reason backward in their search for a solution (Ericsson & Charness, 1994). This is the type of reasoning characteristic of Gf (Horn & Blankson). In contrast, experts tend to employ deductive or forward reasoning. This type of reasoning relies on the complex, stored knowledge that is characteristic of Gc. According to Ericsson and Charness (1994, p. 734), "experts form an immediate representation of the problem that systematically cues their knowledge."

A 1993 study by Rabbitt illustrates the relationship (or rather the lack thereof) between Gf and expert performance. Rabbitt examined the relationship between age, Gf, and the ability to solve crossword puzzles. Among novices, puzzle performance was negatively correlated with age (r = -.25) and strongly correlated with Gf (r = .72). However, among crossword experts, puzzle performance was positively correlated with age (r = .24) and uncorrelated to Gf. Gf appears to play little role in performance among experts. Thus, fluid abilities become less important as crystallized abilities develop. Experts continue to develop these complex, domain-specific crystallized knowledge structures over their lifetimes. For example, Charness (1981) showed that older expert chess players were able to identify optimal chess moves with less planning than younger expert players of approximately the same skill level. Charness suggests this is possible because older experts have more extensive domain knowledge.

Horn and Blankson (2005, p. 61) argue that

> it is possible that increase in expertise abilities necessarily results in decline in nonexpertise abilities, for the devotion of time, energy, and other resources to the development of expertise may of necessity take time, energy, and other resources away from maintenance of Gf, SAR, and Gs.

However, Ericsson and Charness (1994, p. 731) review evidence which suggests another possibility: "acquired skill can allow experts to circumvent basic capacity limits of short term memory and of the speed of basic reactions, making potential basic limits irrelevant."

Age and Job Performance

Research on age and job performance also supports the idea that crystallized ability is superior to Gf in determining job performance. In a recent meta-analysis, Ng

and Feldman (2008) found that age showed a small positive relationship with supervisor-rated task performance ($\rho = .03$). Given that Gf declines substantially with age, a negative relationship between age and job performance would be expected if Gf were the dominant ability. The age – task performance relationship observed by Ng and Feldman is more consistent with a dominant predictive role being played by Gc, since it is maintained throughout most of adulthood.

Elkhonon Goldberg, a neuropsychologist and former student of Alexander Luria, develops a similar line of reasoning in his 2005 bestseller *The Wisdom Paradox*. He reviews extensive neuroscience research which suggests that individuals can continue to make substantial contributions to knowledge and society well into old age, even in the face of organic brain disorders such as dementia. Noted examples throughout history have included Ronald Reagan, Joseph Stalin, and the artist Willem de Kooning. According to Goldberg, this is possible because as individuals grow older, they are increasingly able to access knowledge organized and stored in long-term memory. As people age they increasingly view problems not as novel challenges (Gf), but rather as recognizable patterns that they have previously encountered (Gc). Other researchers have observed that expert chess players (Charness, 1981; Chase & Simon, 1973; de Groot, 1946/1978), physicians (Norman et al., 1992; Patel & Groen, 1991; Schmidt et al., 1990) and physicists (Larkin, McDermott, Simon, & Simon, 1980) solve problems in much the same manner. In his recent book, *The New Executive Brain*, Goldberg (2009) reviews theoretical and empirical evidence which suggests that novel problem solving (i.e., Gf) is handled by the right side of the brain while pattern recognition (i.e., Gc) is handled by the left side of the brain.

Primary Hypotheses

In sum, current theory and empirical evidence supports the following hypothesized patterns of criterion-related validity:

Hypothesis 1a: Compared to fluid ability (Gf) measures, crystallized ability (Gc) measures will more strongly predict academic performance.

Hypothesis 1b: Compared to fluid ability (Gf) measures, crystallized ability (Gc) measures will more strongly predict vocational training performance.

Hypothesis 1c: Compared to fluid ability (Gf) measures, crystallized ability (Gc) measures will more strongly predict job performance.

Although validities for Gf and Gc measures will be analyzed separately whenever possible, many extant measures of cognitive ability do not measure Gf or Gc separately. These assessments are "blended measures" that tap both fluid and crystallized abilities, either proportionately or disproportionately. Such assessments are often presented as General Cognitive Ability or overall IQ (e.g., Full-Scale WAIS IQ). As previously noted, Hunt (2000, p. 126) has argued that many ability assessments used for selection are likely to have a heavy Gc loading. This line of reasoning is supported by scholars such as McGrew (1997, 2005) and Alfonso et al. (2005) who have noted that historically, many of the major test batteries have not included adequate measures of Gf.

In essence, overall, blended, or GCA estimates are composites of their constituent indicators. According to *g* theory, the General Mental Ability factor emerges when two or more specific abilities are measured. As noted previously, specific abilities (such as verbal, quantitative, or technical ability) are merely indicators of a latent general factor.

Gf and Gc are also indicators of this latent general factor g. The larger and more diverse the number of indicators used, the more construct valid will be the final estimate of g. In turn, the g measure should be a stronger predictor of performance when tests sample from a diverse set of cognitive abilities rather than a single, narrow, specific aptitude. That is, as the number of indicators of g increases, so does its predictive power. Using this line of reasoning, a cognitive test measuring both fluid and crystallized ability should be a better measure of g than either fluid or crystallized ability in isolation. In sum, because they sample from more abilities (or indicators), blended, or GCA measures are expected to be stronger predictors of performance than Gf measures, and equal or stronger predictors of performance than Gc measures:

> *Hypothesis 2a*: Overall, blended, or GCA measures will be stronger predictors of academic performance than fluid ability (Gf) measures, and equal or stronger predictors of academic performance than crystallized (Gc) measures.

> *Hypothesis 2b*: Overall, blended, or GCA measures will be stronger predictors of vocational training performance than fluid ability (Gf) measures, and equal or stronger predictors of vocational training performance than crystallized (Gc) measures.

> *Hypothesis 2c*: Overall, blended, or GCA measures will be stronger predictors of job performance than fluid ability (Gf) measures, and equal or stronger predictors of job performance than crystallized (Gc) measures.

Testing these hypotheses will provide important information regarding which indicators are more closely related to academic, training, and job performance. That is, testing these hypotheses will increase our understanding of whether or not one's performance at school and in the workplace is linked more closely to the ability to solve novel problems (Gf), or whether it is more strongly linked to his or her ability to establish and access patterns of acquired knowledge and information in the environment (Gc). Furthermore, since both Gf and Gc tests are currently being used for assessment and selection purposes, obtaining accurate estimates of operational validity will provide practitioners with useful information for choosing the most efficient selection tool.

<u>Supplemental and</u>
<u>Confirmatory Hypotheses</u>

High vs. Low Stakes Testing

One of the assumptions underlying ability testing is that individuals exert maximal effort during testing. Thorndike (1924, p. 224) captured this idea nearly a century ago: "All our measurements assume that the individual in question tries as hard as he can to make a high a score as possible…however, we rarely know the relation of any person's effort to his possible maximum effort." Revelle (1993, pp. 352-353) has noted that "although individual differences in cognitive ability are assumed to exist, differences in motivation are ignored." Nevertheless, test motivation may impact the means and standard deviations of cognitive test scores. In a recent *Proceedings of the National Academy of Science* article, Duckworth and colleagues (Duckworth, Quinn, Lynam, Loeber, & Stouthamer-Lober, 2011) have argued that under certain

circumstances, differences in motivation will affect not only the scores on cognitive tests, but their validities as well.

A major factor that may affect test motivation is the circumstances or stakes of the testing. Although most individuals should be motivated during high stakes testing (such as when tests are administered for selection or promotion purposes), individuals may be less motivated when tests are administered for low-stakes purposes such as research. Duckworth et al. (2011) recently examined the role of test motivation in intelligence testing in a two-part study. Their first study was a meta-analysis ($k = 46$, N = 2,008) which examined the role of incentives on IQ test scores. They found that offering incentives to test-takers resulted in higher mean baseline IQ scores ($g = .64$, 95% CI = .39 - .89)[3]. Further, this effect was stronger for samples with a lower mean IQ ($g = .94$, 95% CI = .54 – 1.35) vs. a higher mean IQ ($g = .26$, 95% CI = .10 – .41). Thus, test motivation appears to be more of an issue with lower IQ subjects. It is important to note that the majority of the subjects included in the analysis were children under the age of 12 who were offered monetary or other incentives for better test performance. It is unclear whether or not this effect would also be visible when scores on high stakes (selection/assessment) vs. low stakes (research) tests are compared in a natural or field setting.

Duckworth et al.'s (2011) second study examined the relationships between IQ, test motivation, and subsequent life outcomes (academic achievement, criminal convictions, employment) in a sample of 251 adolescent boys (mean age = 12.5) from the

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Note: g = Hedge's gamma, a value comparable to Cohen's d, but corrected for small-sample size

Pittsburgh Youth Study. Each subject was videotaped while taking a short form of the

Wechsler Intelligence Scale for Children (WISC-R). The test motivation of the subjects

was rated by trained observers who viewed 15-minute, thin-slice video segments for each

subject. Follow-up information was attained in early adulthood (ages 24-26). IQ and

ratings of test motivation were found to correlate at .26. Further, IQ and ratings of test

motivation (TM) were both found to correlate with a number of outcomes including

academic performance (r IQ = .70, r TM = .31), years of education (r IQ = .47, r TM =

.24), employment (r IQ = .21, r TM = .21), and criminal convictions (r IQ = -.42, r TM =

-.18). The authors used structural equation modeling to examine the effects of IQ and

test motivation. Their results suggested that "failing to account for the influence of

motivation on IQ scores resulted in an overestimation of the association between latent

intelligence and all four life outcomes…" (Duckworth et al., 2011, p.7718). This effect

was less pronounced for academic outcomes (academic achievement, years of education)

than for nonacademic outcomes (employment, criminal convictions). In addition, the

authors point out that after controlling for test motivation, intelligence remained a

statistically significant predictor for all outcomes. Drawing on the results of both studies,

Duckworth et al. (2011, p. 7718) concluded that

> test motivation poses a less serious threat to the internal validity of
> studies using higher-IQ samples, such as college undergraduates…
> On the other hand, test motivation may be a serious confound in
> studies including participants who are below-average in IQ and
> who lack external incentives to perform at their maximal potential.

Duckworth et al's findings suggest that for high school students, cognitive ability

tests should display lower observed validities under high stakes testing conditions since

the test motivation of subjects should be more uniform. Given this, standard deviations

of cognitive tests administered under high stakes conditions should be smaller, resulting in greater range restriction (i.e., smaller u_x values). In contrast, cognitive ability tests should demonstrate higher observed validities under low stakes testing conditions due to the variable effects of test motivation, which in turn produce more variability in test scores (i.e., higher u_x values). In college samples, low stakes and high stakes cognitive ability tests should demonstrate similar validities, since students in these samples tend to have higher IQs and research has demonstrated that test motivation has less of an effect on test scores for high ability individuals.

Given this, the following supplemental hypotheses are proposed:

Hypothesis 3a: For high school students, compared to high stakes cognitive ability tests, low stakes cognitive ability tests will display larger observed validities.

Hypothesis 3b: For college students, high stakes and low stakes cognitive ability tests will demonstrate similar observed validities.

Occupational Complexity

Although cognitive ability is a valid predictor of job performance across all occupations, previous research has shown that this validity increases as the level of occupational complexity increases (e.g., Ghiselli, 1973; Hunter, 1980; Hunter & Hunter, 1984). The general argument for the observed phenomenon is that cognitive ability tests are more valid predictors in complex jobs because these jobs have greater cognitive demands (Hunter & Hunter, 1984; Schmidt & Hunter, 1998). In contrast, Hunter (1980; Hunter & Hunter, 1984) has shown that psychomotor tests demonstrate the opposite

pattern of validities. That is, the validity of psychomotor tests increases as job complexity decreases.

The most compelling evidence that cognitive test validities increase with complexity has been presented by Hunter (1980; Hunter & Hunter, 1984), and is based on his analysis of General Aptitude Test Battery (GATB) validity data. Using 515 GATB validity studies, Hunter classified occupations into five complexity families using an adaption of Fine's (1955) Data/Things dimensions that are available for all jobs in the *Dictionary of Occupational Titles*. Hunter found that the validity of cognitive ability for predicting job performance varied between categories, ranging from .23 for feeding/ offbearing jobs (low complexity jobs such as shrimp picker and cannery worker) to .58 for synthesizing/coordinating jobs (high complexity jobs such as biologist). However, some scholars have questioned the adequacy of the five job families that Hunter utilized (e.g., Hartigan & Wigdor, 1989). Given this, occupations in the current study will be classified using the O*NET Job Zone system, which is described in detail in the following chapter. Validities will then be assessed for high, medium, and low complexity jobs.

Interestingly, a similar gradient has not been observed for training performance (Hunter, 1980; Hunter & Hunter, 1984). That is, when training performance is the criterion, cognitive test validities at different complexity levels tend to be similar. This finding suggests a potential ceiling effect, whereby cognitive ability predicts at or near its maximum across all training situations. Given that Hunter's meta-analytic results were based on a large number of primary studies (all of which used the GATB as a predictor), a confirmatory hypothesis was developed along these lines (Hypothesis 4a).

Nevertheless, some studies have found that cognitive ability is a stronger predictor of training performance for more complex occupations. For example, Brown, Le, and Schmidt (2006) examined the validity of the ASVAB for predicting performance in a number of Navy training schools. They found that the validity of cognitive ability increased as the complexity of the training program increased. Specifically, they found that the zero-order correlation between cognitive ability validity and length of training program (a proxy measure for complexity) was .77 while the zero-order correlation between cognitive ability validity and the ability requirements of the occupation (as rated by experts) was .33. Brown et al.'s finding suggests that the observed training validity gradient may reflect the increased cognitive demands of more complex occupations.

Based on the previous research, the following confirmatory hypotheses are proposed:

> *Hypothesis 4a*: Cognitive ability measures will demonstrate similar validities for training performance across job complexity levels.

> *Hypothesis 4b*: Cognitive ability measures will be stronger predictors of job performance for higher complexity occupations vs. lower complexity occupations.

I describe the methods that I used to examine the primary and supplemental hypotheses in the chapter which follows.

CHAPTER 4

METHODS

Chapter Overview

In this chapter I present the methods that I used to test the hypotheses presented in the previous chapter. First, I provide an overview of how academic, training, and job performance were operationalized in the current study. Next, I describe the literature search process, coding procedures, and potential moderators. I then discuss the general meta-analytic strategy I employed, as well as procedures for addressing data duplication, predictor and criterion unreliability, and range restriction.   I conclude the chapter by reviewing the hypotheses developed in Chapter 3, and then describing how I tested each of these hypotheses.

Operationalization of Criteria

Academic Performance

Individuals in the developed world spend a large portion of their early lives in school. Consequently, a great deal of effort goes into evaluating academic performance. A number of performance measures have been developed to measure academic success. For example, in secondary school and college, academic performance can be measured using grades, class rank, graduation status, membership in academic honor societies, and performance on standardized achievement tests. These measures are also used to assess performance at the graduate level, in addition to indicators such as faculty ratings,

comprehensive exam performance, number of publications, and time to degree completion (Kuncel, Hezlett, & Ones, 2001).

However, at all educational levels grades are by far the most frequently used method for assessing academic performance (Aiken, 1963; Fishman & Pasanella, 1960; Hoyt, 1965; Kuncel et al., 2001). As Hoyt (1965) notes, grades are often the *only* way performance is measured. Although grades are typically considered as criterion measures of academic performance, they have also been shown to be useful as *predictors* of future academic (e.g., Harris, 1940; Hezlett et al., 2001; Kuncel et al., 2001) and occupational performance (Dye & Reck, 1988, 1989; Roth, Bevier, Switzer, and Schippmann, 1996; Roth & Clarke, 1998). Further, research suggests that many hiring managers consider applicants' grades when making employment decisions (Campion, 1978; Brown & Campion, 1994; Dipboye, Fromkin, & Wiback, 1975; Oliphant & Alexander, 1982; Reilly & Warech, 1993; Rynes, Orlitzky, & Bretz, 1997; Thoms, McMasters, Roberts, and Dombrowski, 1999; Zikmund, Hitt, & Pickens; 1978), with higher grades typically leading to more favorable evaluations (however, see McKinney, Carlson, Mecham, D'Angelo, and Connerley (2003) for a contrarian perspective).

Kuncel (2001) offers several additional reasons why grade point averages (GPAs) are preferred measures of academic performance. First, GPAs reflect not only content mastery, but also persistence and motivation. GPAs are largely under students' own control and most students perceive them as important. Second, GPAs are based on multiple ratings (course grades) based on multiple performance measures (exams, projects, papers, etc.) assigned by multiple raters (instructors). Third, GPAs reflect performance over an extended time period. Kuncel argues that these characteristics

produce "a number of desirable results" such as relatively high internal consistency reliabilities and temporal stability (p. 25). Based on these factors, and its wide availability, GPA was chosen as the academic performance criterion of interest in the current study.

<div align="center">Training Performance</div>

Goldstein (1980) defines training as the "acquisition of skills, concepts, or attitudes that results in improved performance in an on-the-job environment" (p. 230). A key component of this definition is its emphasis on application within work contexts, a core feature which distinguishes training from broader, yet related, concepts such as learning. Organizations invest in training to improve performance at the individual, team, and organizational levels, and "as organizations strive to compete in the global economy, differentiation on the basis of the skills, knowledge, and motivation of their workforce takes on increasing importance" (Aguinis & Kraiger, 2009, p. 452).

Investments in training are far from trivial (e.g., Bassi & Van Buren, 1999; McKenna, 1990). For example, a recent American Society of Training and Development (ASTD) report (Paradise, 2008) estimates that despite the economic downturn, firms in the United States spent in excess of $134 billion, or an average of $1,068 per employee, on employee learning initiatives in 2008. As these are only estimates for the U.S., the total financial investment in training across the globe is substantially greater.

Although a number of frameworks have been proposed for evaluating training programs, Donald Kirkpatrick's four-level model (1959a, 1959b, 1960a, 1960b) has been the one most frequently adopted by practitioners (Alliger, Tannenbaum, Bennett, Traver,

& Shotland, 1997; Sugrue & Rivera, 2005; Twitchell, Holton, and Trott, 2001).

Although Kirkpatrick has subsequently revised and expanded upon his original

contribution (e.g., Kirkpatrick. 1976; Kirkpatrick, 1996; Kirkpatrick, 1998), his training

evaluation approach "has remained basically the same" (Kirkpatrick, 1996, p. 54).

Kirkpatrick's four levels are concerned with trainee reactions, learning, transfer, and

financial and organizational results following training program implementation.

Despite its popularity among practitioners, Kirkpatrick's model has been

criticized for being atheoretical. Accordingly, additional theory-based models of training

evaluation have been developed. One of the most established of these models is the one

proposed by Kraiger, Ford, and Salas (1993). Kraiger et al.'s model focuses on learning

as the primary objective of training (c.f., Campbell, 1988; Shuell, 1986). Kraiger et al.

propose a classification scheme by which learning can be classified into three categories

of outcomes: cognitive outcomes, skill-based outcomes, and affective outcomes.

Cognitive outcomes are the primary training criteria of interest in the current study.

These include verbal knowledge, knowledge organization, and cognitive strategies.

Cognitive outcomes are most frequently assessed via exams, the results of which are

often reported as grades. Skill-based outcomes focus on compilation and automaticity.

Skills are often measured using behavioral observation or skills testing. Finally, affective

outcomes are concerned with the attitudinal and motivational states of trainees. The

affective category includes "all those learning outcomes that that are neither cognitively

based nor skill based" (Kraiger et al., 1993, p. 319). According to the Kraiger et al.

typology, the affective learning outcome category can be distinguished from reaction

measures (e.g., satisfaction with training or "smile sheets," Alliger et al., 1997; Brown,

2005; Kirkpatrick, 1998). Although they are not included in the affective learning outcomes category, reaction data can indeed be useful to organizations (Brown, 2005; Brown & Gerhardt, 2002; Ford & Wroten, 1984; Kraiger, 2002). Despite their utility, both affective learning outcomes and reaction measures were considered to be beyond the scope of the current study.

Job Performance

Contemporary scholars consider job performance to be a multidimensional construct (e.g., Campbell, McHenry, & Wise, 1990; Hattrup, O'Connell, & Wingate, 1998; Motowidlo & Van Scotter, 1994; Murphy, 1989; Rotundo & Sackett, 2002; Viswesvaran & Ones, 2000), although there does also appear to be a general factor in job performance ratings (Viswesvaran & Ones, 2000; Viswesvaran, Ones, & Schmidt, 2005). In the current study, job performance was classified as either overall job performance, or into one of the three broad dimensions of job performance outlined by Viswesvaran and Ones (2000) and Rotundo and Sackett (2002). These dimensions include task performance (Borman & Motowidlo, 1997; Fleishman, 1967; Motowidlo & Van Scotter, 1994; Murphy, 1989), organizational citizenship behavior (OCB; Brief & Motowidlo, 1986; LePine, Erez, & Johnson, 2002; Organ, 1997; Podsakoff, MacKenzie, Paine, & Bachrach, 2000), and counterproductive work behavior (CWB; Gruys & Sackett, 2003; Ones, Viswesvaran, & Schmidt, 1993; Robinson & Bennett, 1995; Sackett, 2002). Although alternative models of job performance do exist (e.g., Griffin, Neal, & Parker, 2007), the task performance – OCB – CWB taxonomy is the most widely accepted and

utilized in the management and applied psychology literatures (Aguinis, 2008).

Accordingly, the current study used these as measures of job performance.

Literature Search

An extensive search was conducted to locate published and unpublished research

that has examined the relationship between cognitive ability and any of the three criteria

of interest: academic performance, training performance, or job performance. Multiple

search methods were utilized. These methods are described below.

Electronic Database Searches

Ben Postlethwaite and Tamara Giluk conducted a comprehensive search of

PsycINFO (1887 – 2009) using a combination of predictor and criterion keywords.

Predictor keywords included *cognitive ability, general mental ability, intelligence, fluid*

intelligence, and crystallized intelligence. Criterion keywords included *performance,*

academic performance, grades, GPA, training performance, job performance. This

initial search resulted in over 26,000 abstracts. Each abstract was examined for relevance

and copies of over 1,000 potential studies were obtained. In addition, similar paired

keyword searches were conducted using Google Scholar.

Electronic searches were also conducted using additional databases including

EBSCOhost (Academic Search Elite), ProQuest, ERIC, JSTOR, and Web of Science as

well as publisher-specific databases including Elsevier ScienceDirect, Emerald Library,

Informaworld, IngentaConnect, and Wiley Interscience.   An extensive search for

unpublished dissertations and theses from the United States was made using ProQuest

Dissertations and Theses. Foreign dissertations were located using electronic resources such as the Australasian Digital Theses Program, EThoS (United Kingdom), Theses Canada, and the Center for Research Libraries Foreign Doctoral Dissertations.

Manual Searches

In addition, reference lists from prior qualitative (e.g., Harris, 1940) and meta-analytic reviews (e.g., Aamodt, 2004, 2011; Bertua et al., 2005; Donnon, Paolucci, & Violato, 2007; Hunter & Burke, 1994; Kuncel et al., 2001, 2004, 2007; Sackett, Kuncel, Arneson, Cooper, & Waters, 2009; Salgado et al., 2003a, 2003b) and from all articles identified for inclusion were searched manually along with the CVs of researchers active in this area. A manual search of key education and psychology journals was also conducted. These journals included *Educational and Psychological Measurement, Journal of Applied Psychology*, and *Personnel Psychology*. Finally, reverse citation searches of prior reviews, book chapters, and studies previously identified for inclusion were conducted using Web of Science and Google Scholar. To date, approximately 1,800 potentially usable studies have been located using the search strategies described above. This total includes over 400 of the original written reports for the General Aptitude Test Battery (GATB) validation studies conducted by the United States Employment Service between the late 1940's and early 1970's. A somewhat larger set of these studies (some of the original written reports are no longer publicly available) was previously analyzed by Hunter (1980, $k = 515$). The 515 Hunter studies, along with an additional 264 newer GATB studies were analyzed by a special National Research

Council committee tasked with investigating the validity of the GATB (Hartigan and Wigdor, 1989).

Inclusion Criteria

Each study identified during the literature search as having potential for inclusion was evaluated against several a priori criteria. First, the study must have included at least one measure of psychometric cognitive ability (e.g., fluid intelligence, crystallized intelligence, general cognitive ability, IQ). Studies reporting results for specific cognitive abilities or aptitudes (e.g., Brown, Le, & Schmidt, 2006) were retained if the specific abilities, or a composite of those abilities, could be classified as being a measure of fluid ability, crystallized ability, or general cognitive ability. Consistent with previous research (e.g., Frey & Detterman, 2004; Koenig, Frey, & Detterman, 2008; Kuncel et al., 2004; Sackett, Borneman, & Connelly, 2008), well-established examinations used for undergraduate and graduate admissions purposes were treated as measures of cognitive ability. Examples of such examinations used for admissions at the undergraduate level include the ACT Assessment, the American Council on Education (ACE) Psychological Examination, the Ohio State University Psychological Examination, and the Scholastic Aptitude Test (SAT). Standardized examinations utilized at the graduate level include the Dental Admission Test (DAT), Graduate Management Admissions Test (GMAT), Graduate Record Examination (GRE), Law School Admission Test (LSAT), Miller Analogies Test (MAT), and Medical College Admissions Test (MCAT). In addition to containing a measure of cognitive ability, each study must have reported a correlation between cognitive ability and one of the three performance criteria of interest: academic

performance, training performance, or job performance. If correlations between

cognitive ability and any of the three performance criteria were not provided, the study

must have reported alternate statistics that permit the calculation of correlations

(standardized mean difference scores, χ^2 values, t or F test results). Further, to qualify for

inclusion in the meta-analysis, each study had to report sample size(s). Finally, to qualify

for inclusion, cognitive ability measures must have been obtained by the researchers

either directly (e.g., assessments administered by the researchers) or from reliable

archival sources (e.g., IQ scores found in official school records). Studies containing

only self-reported ability or admissions test scores were excluded.

When academic performance was the criterion, studies must have included some

measure of grades at the course, semester, or cumulative level (e.g., GPA), or have

reported student rankings that were determined solely on the basis of grades. Likewise,

grades must have been reported at the secondary level (U.S. high school grades 9-12 or

equivalent) or higher. Studies that only reported grades from students enrolled in

elementary or junior high schools (U.S. grades K-8 or equivalent) were excluded from

consideration. Likewise, for the purposes of the current study, studies examining

cognitive ability and graduate student performance were excluded. Thus, this study

examines the relationship between cognitive ability and academic performance for high

school and college students.

Although research has shown that self-reported grades are fairly consistent with

grades obtained from official school records (Kuncel, Credé, & Thomas, 2005), studies

were excluded if the grades reported were not obtained from official sources.

Furthermore, some studies have utilized alternate measures of academic performance

such as standardized achievement test scores, time to degree completion, and graduation status. Such studies were excluded if a measure of grades was not also reported.

When training performance was the criterion, studies must have reported some measure of cognitive, skill-based, or overall training performance (final training course grade) that was obtained during or following completion of a vocational or on-the-job training program. Since this dissertation focuses on the relationship between cognitive ability and real-world performance, training studies conducted in a laboratory setting were excluded. Studies containing only self-reports of learning following training were excluded, as were affective reactions to training.

When job performance was the criterion, studies must have reported some measure of objective (e.g., sales performance, productivity, absences) or subjective (e.g., peer or supervisor ratings of performance) job performance. Subjective job performance was considered broadly, and included the dimensions described earlier: task performance, organizational citizenship behavior (OCB), counterproductive work behavior (CWB), and overall job performance. Studies containing only self-rated job performance were excluded.

<div align="center">Data Set Reduction</div>

Given the very large number of primary studies identified and obtained during the literature search, the committee supervising this thesis suggested that I test the study hypotheses using a representative sample of primary studies. Accordingly, for each criterion of interest at least 100 independent samples (or the maximum number of samples if $k < 100$) of Gc and GCA were coded and analyzed. For each criterion of

interest, all of the Gf samples identified during the literature search were coded and analyzed. Likewise, when either training or job performance was the criterion, all of the GCA samples identified during the literature search phase were coded. For the remaining predictor – criterion pairs (GCA and academic performance; Gc and academic, training, and job performance) a representative sample of primary studies was selected. In choosing these studies, emphasis was placed on the extent to which the predictor measures were a good measure of either Gc or GCA. Studies in which scales were not adequately described were eliminated. Further, an attempt was made to draw studies from multiple time periods. Finally, studies were not selected based exclusively on the above factors and not on their reported validities. In sum, while these studies were not chosen purely at random, they are representative of those found in the larger data set.

The final data set consisted of validities gathered from 419 unique primary studies. Some studies contained multiple independent samples. Likewise, some studies reported data for both job and training performance. Details for the final data set are as follows:

Academic Performance (132 studies)

- Gf – 34 studies ($k = 67$, $N = 7,991$)

- Gc – 65 studies ($k = 157$, $N = 199,642$)

- GCA – 54 studies ($k = 110$, $N = 29,739$)

Training Performance (81 studies)

- Gf – 15 studies ($k = 20$, $N = 3,724$)

- Gc – 65 studies ($k = 114$, $N = 38,793$)

- GCA – 18 studies ($k = 24$, $N = 7,563$)

Job Performance (229 studies)

- Gf – 12 studies ($k = 23$, $N = 3,273$)

- Gc – 156 studies ($k = 199$, $N = 18,619$)

- GCA – 53 studies ($k = 84$, $N = 8,070$)

<u>Coding</u>

The coding of studies entailed a two phase process. The first phase involved the initial coding of primary studies according to predetermined criteria. The second phase was concerned with classifying each cognitive ability measure identified in the first phase into one of three types of ability: fluid, crystallized, or general cognitive ability. Each phase will be discussed in turn.

Phase One:
Initial Coding of Studies

Each primary study was coded for basic variables including author(s), year, journal/publication title with volume and page numbers, and outlet type (e.g., journal article, conference presentation, book chapter, technical manual, thesis/dissertation). For each independent sample reported in the study, a brief description of the sample was recorded along with sample size, the country of data collection, and a summary of demographic details (sex, race, and age). All relevant predictors and criteria were listed, along with means, standard deviations, and reliabilities (and reliability type) when such information was provided. Time intervals between the collection of predictor and criteria measures were recorded if reported in the primary study. Relevant moderators were coded according to the guidelines presented later in this chapter. For each predictor-

criterion relationship, correlations, or other measures of effect size converted to correlations, were recorded. During this phase, cognitive ability measures (predictors) were recorded by assessment name and test form (e.g., GATB - General Aptitude Test Battery - Form B-1001; or, Raven's Advanced Progressive Matrices – 1938 Series). As unique cognitive ability measures were encountered, they were added to a master list containing all cognitive ability measures.

I personally coded the majority (>80%) of samples included in the data set. To assess coding reliability, a minimum of 10% of all independent samples were double coded by an additional trained coder (Tamara Giluk). Initial agreement on key coding categories (e.g., study design, cognitive ability measure, criteria, and effect size) exceeded 95%. Any disagreements were resolved through discussion. Dr. Giluk was the sole coder for approximately 20% of the samples included in the final data set, although I frequently verified this data during data entry.

Phase Two: Classification of Cognitive Ability Measures.

During the second phase, in consultation with Frank Schmidt, Tamara Giluk and I classified each unique cognitive ability measure identified in Phase One into one of three ability categories: fluid, crystallized, or general cognitive ability. Cognitive ability measures not classified into one of these categories were disregarded for the purposes of the current study. After agreement on measure classification was reached, the classification information was matched to the Phase One data. It was believed that classifying cognitive ability measures separately after all the unique tests had been identified increased the accuracy of coding decisions, as all attention was devoted to the

task. Furthermore, additional details about the nature of the measures emerged throughout the phase one coding process. In situations where the classification of a measure was unclear, the measure in question was discussed with Frank Schmidt. An effort was made to only retain measures that clearly reflected the constructs of fluid, crystallized, and general cognitive ability.

Measure classification was guided by previous research. Certain tests such as Raven's Progressive Matrices and Cattell's Culture-Fair Intelligence Test are well-established measures of fluid ability, while the Mill Hill Vocabulary Scale is considered an established measure of crystallized ability. For example, Carpenter, Just, and Shell (1990) conducted a thorough analysis of the cognitive processes required to score highly on the Raven's tests. They confirmed that the Raven's primarily measures the ability to discern abstract relations and manage problem solving goals in working memory, processes consistent with the definition of fluid ability.

We also utilized McGrew's (1997) cross-battery classification system. McGrew provides a comprehensive framework which classifies the scales found in major intelligence test batteries according to the CHC Gf-Gc model. These batteries include the Kaufman Adult Intelligence Test (KAIT), the Wechsler Adult Intelligence Scale (WAIS), the Woodcock Johnson-Revised test (WJ-R), and the Differential Abilities Scale (DAS). Similarly, Ackerman et al. (2005, Appendix) also present a framework for classifying a number of frequently encountered cognitive ability measures. When existing frameworks did not provide information with regard to how a test should be classified, supplemental material such as test manuals, *Buros Mental Measurement Yearbook*, and factor analytic evidence were consulted. In some cases, our classification decisions ran contrary to the

stated viewpoints of the primary study authors. For example, Furnham and colleagues (e.g., Chamorro-Premuzic & Furnham, 2008; Furnham & Monsen, 2009) have frequently utilized the three-minute Baddeley Reasoning Test as a measure of fluid intelligence. However, upon closer examination we determined that the Baddeley test is more likely a measure of working memory, a construct shown to be related to but distinct from Gf (c.f., Ackerman et al., 2005). The final classification of cognitive ability measures according to Gf, Gc, and GCA are presented in Appendices A.

Moderators

The magnitude of relationship between cognitive ability and performance may vary according to factors related to the nature of the predictors or criteria, as well as to factors related to the subjects and research settings. To explore these possibilities, studies were coded for a number of relevant potential moderators to be examined in the current study, or at a time in the future. For the purposes of this dissertation, primary emphasis will be placed on testing the hypotheses presented in Chapter 3. However, a number of potential moderators were also coded in order to facilitate the examination of additional research questions after the current study has been completed. In order to minimize second-order sampling error (Hunter & Schmidt, 2004), moderators should usually only be examined when $k \geq 5$ or when the overall sample size is large enough to reduce second-order error. However, in some cases moderators with $k < 5$ and a small total sample size are presented for illustrative purposes. Such results should be interpreted with caution. Moderators were examined hierarchically where sample size permits.

While some of the proposed moderators apply to all studies, others are specific to the performance criteria of interest. Proposed moderators are described below.

<center>Moderators Relevant to All Studies</center>

To facilitate an examination of potential publication bias in future work with this data set, the publication status of each primary study was coded as either published or unpublished. Studies appearing in peer-reviewed journals were coded as published. Conference papers, technical reports, dissertations, and theses were coded as unpublished.

As noted previously, studies were coded with regard to the specific cognitive ability measures used. In addition to facilitating assignment to fluid, crystallized, and general cognitive ability categories, this coding scheme permits the analysis, reporting, and comparison of test-specific validities for commonly used cognitive ability tests. In the current study, specific test validities (and validities for families of like tests) were examined for measures of fluid ability.

Each study was coded with regard to the year of data collection. When date information is reported by the primary study author, it was recorded as such. If the data collection date was not reported, and there was no indication that the data was archival in nature, the year of data collection was calculated as the year of publication minus two years. This information will allow the validities and u_x values of cognitive ability measures to be examined over time (e.g., decades or other meaningful time periods). Although they are beyond the scope of the current study, moderator analyses for time may be interesting given that this data set includes nearly 100 years of validity data.

Examining validities over time may also inform our understanding of the Flynn effect, as well as address recent assertions by Schmitt (2007) that the validities of cognitive tests may have shifted over time due to changes in predictor quality and the nature of work itself. With regard to Schmitt's claim, Schmidt, Le, Oh, and Shaffer (2007, p. 64) have countered that examining the validity of cognitive ability over time is unlikely to change our current understanding of GMA and work performance, arguing that "changes over time in the nature of work and jobs, including changes in the employee-employer psychological contract, have not resulted in any noticeable changes in the role that mental ability plays in job performance."

<div align="center">

Moderators Relevant to
Academic Performance

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It is well established that the validity of cognitive ability for predicting academic performance decreases as educational level increases (Jensen, 1998; Kuncel, 2003). Several explanations for this phenomenon have been proposed. First, samples become increasingly range restricted at higher educational levels due to the fact that some students with lower cognitive ability levels choose not to continue their studies, while others are not allowed to. Further, there is less variability in the grades that are assigned at higher levels of study. For example, in many graduate programs almost all students earn A's and B's. Finally, there is some evidence that at higher levels of study, certain (often less capable) students may select less demanding classes and programs of study (c.f., Elliott & Strenta, 1988; Strenta & Elliott, 1987). Accordingly, for each study that examines academic performance, samples will be coded according to the level of study (High School or Undergraduate).

Recent research by Berry and Sackett (2009) suggests that standardized tests are better predictors of individual course grades (ICGs) compared to cumulative GPAs. They argue that (p. 823):

> using ICGs instead of GPA should yield a less contaminated criterion by holding differences in course selection constant. Certainly, if one is simply interested in predicting GPA, then predicting ICGs is not appropriate. However, if one is interested in assessing how well SAT scores and high school GPAs predict academic performance, of which GPA is just an imperfect indicator, then analyses using ICGs as the criterion should provide a better estimate.

After analyzing the relationship between SAT scores and over 5 million individual course grades for 167,816 students, they found that the percent variance explained by high school grades and SAT scores was 30-40% lower when the criteria were GPAs vs. individual course grades. They attribute this finding both to student course choice and grading idiosyncrasies between instructors.

Given this, each academic performance variable was classified according to whether it represents performance in an individual course vs. performance in multiple courses (such as a single semester GPA or cumulative GPA). When relationships between cognitive ability and single course grades were reported, the academic area of study for the course was coded (e.g., Mathematics, Social Science, Language Arts, etc.). Although individual course grades were coded as they were encountered, the results presented in Chapter 5 are based solely on samples reporting composite grades (GPAs) for at least one academic semester.

Research by Humphreys (e.g., Humphreys, 1968; Humphreys & Taber, 1973) demonstrates that when predicting grades, the validities of cognitive tests are stronger predictors of performance in earlier semesters. That is, cognitively loaded tests correlate

most strongly with freshman grades. This is largely attributable to increased range

restriction in subsequent semesters. For example, Humphreys (1968) found that the

validity of the ACT was .48 for predicting first semester college GPA and .16 for

predicting final (8th) semester GPA. Thus, when single semester or cumulative GPAs

are reported, the average number of units contributing to the overall GPA, or the number

of semesters completed to date, was also recorded. For example, first semester college

grades were coded as UGPA-C1 (cumulative GPA based on one semester) while grades

for student's entire undergraduate career were coded as UGPA-C8 (cumulative GPA

based on eight semesters).

Testing Stakes

Testing stakes were coded when information presented in the primary study

sample allowed such a determination to be made. The perspective of the test taker was

considered when making all high stakes vs. low stakes categorization decisions. When

cognitive ability tests within a sample were administered for selection or assessment

purposes, the sample was assigned to the high stakes category. The high stakes testing

category included traditional academic selection tests such as the ACT, SAT, and PSAT,

as well as cognitive tests administered by schools or universities for assessment or

placement purposes. Samples in which cognitive ability tests were administered

primarily for research purposes were coded as low stakes. Within academic samples,

some tests were used exclusively for high stakes purposes. For example, the ACT and

SAT are administered as high stakes selection tests, and are perceived as such by

examinees. Nevertheless, scores may later be used for research purposes. Within the

academic samples included in this study, some tests such as the Wonderlic Personnel Test

were administered solely for low stakes research purposes. Depending on the individual

primary study, tests such as the Otis Quick Scoring Mental Ability Test or Wechsler Adult Intelligence Scale may have been administered for either low stakes or high stakes purposes.

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Moderators Relevant to
Training Performance

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When training performance was the criterion, performance was coded according to Kraiger et al's (1993) typology. That is, training performance was coded as to whether it represented learning outcomes that were cognitive (knowledge assessed during or following a training program) or skill-based (behavioral/skill demonstrations measured via an assessment center, work sample test, or other subjective skills evaluation made by an instructor or trained rater). Given that the vast majority of training studies in the current data set focused on cognitive knowledge expressed through overall training course grades or post-training exams, the results which follow focus on relationships between Gf, Gc, GCA, and cognitive learning outcomes. However, many primary studies often did not report how an overall training grade was calculated. It is likely that in some of these samples the overall training performance grade represents both cognitive and skill-based learning outcomes. Studies that examined only skill-based learning outcomes were not examined in the analyses which follow.

<div align="center">

Moderators Relevant to Job Performance

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As described earlier, job performance was classified as either overall job performance, or into one of the three broad components of job performance outlined by Viswesvaran and Ones (2000) and Rotundo and Sackett (2002). These components

include task, citizenship (OCBs), and counterproductive (CWBs) performance. However, the number of studies reporting relationships between cognitive ability and CWBs or OCBs was very limited. In a recent search for studies of this type, Schmidt, Shaffer, and Oh (2008) were only able to locate a very small number of studies that examined these variables. Henig (1927), Dilchert, Ones, Davis, and Rostow (2007) and Postlethwaite, Robbins, & McKinniss (2009) are notable exceptions. When multiple measures of job performance were provided, a composite of overall job performance was formed. Additional details regarding calculation of composites are presented in the discussion on conceptual replication later in this chapter.

Research has demonstrated that much of the variance in performance ratings is due to idiosyncratic rater effects (Mount, Judge, Scullen, Sytsma, & Hezlett, 1998; Scullen, Mount, & Goff, 2000; Viswesvaran et al., 2005). Differences may also occur based on whether performance is objectively or subjectively measured. Given this, each job performance criterion was coded as either an objective measure of performance (e.g., sales performance, productivity) or a subjective rating of performance. The majority of studies coded used subjective performance ratings. Subjective performance assessments were further classified according to the source of the ratings: supervisor(s), peer(s), or subordinate(s). Supervisors were the source of ratings for the vast majority of samples that were coded. As noted previously, correlations between cognitive ability and self-reported work performance were not examined in the current study.

Occupational Complexity

Previous meta-analyses have shown that the validity of cognitive ability for predicting training and job performance increases as the level of occupational complexity increases (Hunter, 1980; Hunter & Hunter, 1984, Salgado et al., 2003b; Schmidt & Hunter, 1998). Given these findings, in the current study, samples were coded according to occupation as well as level of occupational complexity. When a sample examined training or job performance for a specific occupation (or group of very similar occupations), the occupation investigated was recorded and matched with a corresponding occupation title and code in the national O*NET database (Peterson et al., 2001). O*NET is a rigorously developed system that has integrated previous job classification information (such as found in the Dictionary of Occupational Titles) with contemporary job analysis data. The O*NET system contains detailed information on over 900 unique occupations. If primary studies reported occupation data in the form of DOT job codes (as is the case with all of the GATB validation studies), these codes were transformed to current O*NET occupation codes using published crosswalks.

Occupational complexity was measured using O*NET job zones (see Le et al., 2011). Trained O*NET staff assign all occupations in the O*NET database to one of five job zones based on the tasks and requirements of the occupation, the education, training, and experience levels required for the occupation, and previously determined complexity levels. For example, occupations in Job Zone 1 require little preparation and less than a high school education. Sample occupations in this job zone include Food Preparation Workers (35-2021.00), Landscaping and Groundskeeping Workers (37-3011.00), and Maids and Housekeeping Cleaners (37-2012.00). In contrast, occupations in Job Zone 5 require extensive skills and education, with most requiring a graduate degree. Sample

occupations in this job zone include Lawyers (23-1011.00), Surgeons (29-1067.00), and

Clinical Psychologists (19-3031.02). For the purposes of this study, the five O*NET Job

Zones were collapsed into three categories representing low (Job Zones 1 and 2), medium

(Job Zone 3), and high complexity occupations (Job Zones 4 & 5). Validities were

analyzed for each of these three levels when the number of independent samples

permitted such an analysis.

An additional advantage of using the O*NET system to classify occupations is

that the system contains extensive data for calculating occupational complexity (as well

as a number of other occupation-relevant constructs) using alternate methods. For

example, Dierdorff and Morgeson (2009) used O*NET to estimate occupational

complexity using 21 items which assess the importance of cognitive ability within each

occupation.

<u>Detection of Duplicate Samples</u>

A basic assumption of meta-analysis is that the effect sizes contained in the

analysis are independent from one another. The existence of duplicate effect sizes within

a meta-analytic data set violates this assumption and "may lead to erroneous conclusions"

(Wood, 2008). Although duplication is frequently mentioned in the context of meta-

analysis, Schmidt (2008, p, 97) argues:

> It is important to be clear that the problem of nonindependent
> studies is not a problem specific to meta-analysis. There is nothing
> about meta-analysis per se that creates this problem. If the
> traditional alternative to meta-analysis—the narrative review—is
> used, duplicate studies are just as much a problem for that method
> of reviewing literatures. The problem of duplicate studies…is a
> problem related to the broader issue of attainment of accurate
> cumulative knowledge in science.

Duplication has been observed in diverse fields of study. When they evaluated 141 systematic reviews in the medical literature, von Elm, Poglia, Walder, and Tramer (2004) observed that 40% of authors had identified duplicate studies. In some cases, articles had been republished up to five times. Duplication has also been observed in the organizational sciences. For example, Stewart and Roth (2004) maintain that Miner and Raju's (2004) meta-analysis of entrepreneurial risk propensity contains dependent samples.

Duplication can take various forms, including dependence of data in longitudinal studies (Gurevitch & Hedges, 1999), reuse of identical or substantially similar data sets to address different research questions (von Elm et al., 2004), and "covert duplication" whereby identical data are republished without citing the original study (Tramer, Reynolds, Moore, & McQuay, 1997; von Elm et al., 2004). Schmidt (2008, p. 97) believes that duplication can likely be attributed, at least in part, to "the greatly increased pressure to publish today, especially among untenured faculty seeking tenure." A cursory examination of the initial set of studies identified for potential inclusion revealed that duplication was likely between several pairs of studies. For example, Allworth and Hesketh (1999) and Allworth and Hesketh (2000) report highly similar correlations between job performance and cognitive ability (measured in both cases using Raven's Progressive Matrices, the Ball Clerical Speed and Accuracy Test, and the Ball Numerical Reasoning Test) in overall samples of 325 hotel employees. In this case, the primary research questions differed between studies, and the later study did cite the earlier publication. Similarly, Dhaliwal and Sharma (1975) and Dhaliwal and Sharma (1976) report identical data on the relationship between cognitive ability and academic

performance in a sample of 75 Indian high school students; however, in this case the 1976 study failed to cite the earlier 1975 publication.

With regard to the statistical effects of duplication, Schmidt (2008, p. 97) states that including duplicate studies in a meta-analysis can "inflate the estimate of the variance of population parameters." When there is lack of independence, total sample size is overestimated and sampling error variance is underestimated. This results in an undercorrection for sampling error and an overestimation of the standard deviation of the population effect size (SD_ρ). In meta-analyses with a small number of effect sizes, duplicate studies can pose a more acute problem by producing second order sampling error. That is, mean effect sizes can be skewed and sampling error variance may be less than what is expected when independence is maintained (Schmidt, 2008).

To date, most researchers have attempted to identify duplicate samples using subjective, informal procedures (Schmidt, 2008). However, Wood (2008) has developed a systematic procedure for detecting duplication. His duplication heuristic (Wood, 2008, Figure 1, p. 81) consists of multiple steps including comparison of authorship, content analysis of methodology, and comparison of sample sizes, response rates, demographics, constructs/measures, and study effects. To detect duplication within the studies identified for inclusion in this dissertation, Wood's duplication heuristic was applied whenever a study shared one or more authors in common with another study. In addition, care was taken to identify duplication that can occur when studies without shared authors analyze a common third-party data set (e.g., the General Social Survey or National Longitudinal Survey of Youth). One limitation of Wood's heuristic is that it does not allow for such a possibility, as studies without shared authors are coded as non-duplicate.

Treatment of Duplicate Samples

Researchers have proposed different methods for handling samples which have been identified as duplicate or non-independent. Although it is sometimes possible to statistically adjust for non-independence (Hedges & Olkin, 1985; Strube, 1987), such adjustments require one to calculate the covariance of the non-independent study effects. However, data for such calculations is rarely available, making such adjustments unfeasible in most cases (Wood, 2008). Other researchers (e.g., Tramer et al., 1997) have proposed using data from only the original or "main" study. Although this approach does eliminate non-independence, it is also problematic in that it may be difficult for meta-analysts to determine which study is the "main study" (Wood, 2008). In addition, utilizing only the main or original study can result in the loss of any data which are reported in only duplicate studies (Schmidt, 2008). According to Wood (2008, p. 92), "some meta-analysts suggest the optimal solution is to aggregate the study effects of the suspected dependent studies." Schmidt (2008, p. 97) agrees with this recommendation, on the basis that aggregating "salvages the information contained in the duplicate studies, while at the same time preserving statistical independence among the entries into the meta-analysis." Accordingly, in the current study, samples identified as duplicates were combined using the methods Hunter and Schmidt (2004, Ch. 10) present for dealing with conceptual replication.

Conceptual Replication

In some studies, multiple assessments of the same cognitive ability type were included for a single independent sample. In such cases, I calculated composite correlations between the multiple predictors and the criterion using the methods described in Hunter and Schmidt (2004) and Nunnally and Bernstein (1994). I followed similar procedures when multiple performance measures of the same type are reported for the same sample. Specifically, I used formula 10.11 provided by Hunter and Schmidt (2004, p.435) when calculating composites:

$$r_{xY} = \frac{\sum r_{xy_i}}{\sqrt{n + n(n-1)\bar{r}}}$$

where x is the single predictor variable, Y is a composite criterion measure derived from the individual criterion measures $y_1, y_2 \ldots y_i,$, n is the total number of individual criterion measures included in the composite measure, and $\bar{r}$ is the average correlation between y measures.

If the scale intercorrelations necessary to compute composite calculation were not available from either the study itself or the literature as a whole, the individual predictor-criterion correlations were averaged to form a single correlation. However, it is acknowledged that this latter method is not ideal as it routinely leads to underestimation of the effect size. In all cases, care was taken to insure that the statistical independence of the samples was maintained.

<div align="center">Meta-Analytic Methods</div>

Mean observed ($\bar{r}$) and corrected correlations ($\bar{\rho}$) were estimated using Hunter and Schmidt's artifact distribution method of meta-analysis (Hunter & Schmidt, 2004).

The Hunter-Schmidt method of meta-analysis assumes a random effects model. Random effects models "allow for the possibility that population parameters (ρ or δ) vary from study to study" (Hunter & Schmidt, 2004, p. 204). In general, meta-analyses based on the random effects model provide more accurate and less biased estimates than meta-analyses based on the fixed-effects model (Field, 2001; Hunter & Schmidt, 2000; Schmidt, Oh, & Hayes, 2009). Further, since population effect sizes are known to vary to some extent in almost all cases, it is almost never appropriate to make the fixed-effects assumption that there will be no variance in population parameters from study to study.

Artifact Data

Predictor Reliability

An initial inspection of a random selection of studies that meet the inclusion criteria reveals that many primary studies failed to report data on the reliabilities of the specific psychometric ability scales that were administered. When reliabilities are reported, they are almost always estimates of internal consistency reliability (Coefficient of Equivalence, e.g., KR-20) or test-retest reliability (Coefficient of Stability). Hunter and Schmidt (2004) maintain that internal consistency reliability estimates (CE) fail to correct for transient error, while test-retest reliabilities (CS) fail to adequately correct for specific factor error. Accordingly, they advocate using the Coefficient of Equivalence and Stability whenever possible. Le, Schmidt, and Putka (2009) extend this logic across multiple scales with the Generalized Coefficient of Equivalence and Stability (GCES). However, CES and GCES estimates are often not readily available for cognitive measures, as many test publishers report only alpha reliabilities. Schmidt, Le, and Ilies

(2003) provide an estimate of the amount of transient error in measures of General

Cognitive Ability (.05 for the Wonderlic Personnel Test). This value was used to adjust

alpha reliabilities to correspond to CES estimates. Thus, all corrections for predictor

measurement error were made using CES estimates rather than coefficient alpha. In

cases where adequate reliability information was not available for a particular type of

measure (e.g., Gf), the reliability value for General Mental Ability was applied.

Previous research has shown that cognitive measures demonstrate acceptable test-

retest reliabilities. For example, based on an examination of 31 GCA test-retest

reliability estimates, Salgado et al. (2003a) estimated a mean unrestricted (applicant)

reliability estimate of .83 (SD_{xx} = .09, mean test-retest interval = 24 weeks).

Nevertheless, since both CE and CS estimates fail to correct for all sources of error, they

should be considered as overestimates of reliability. Similar GCA unrestricted reliability

estimates have been presented by Bertua et al. (2005; r_{xx} = .85, based on a UK data) and

Hunter et al. (2006; r_{xx} = .81, based on Hunter's 1980 analyses of GATB data). In the

current study, an unrestricted r_{xx} value of .83 was used to correct for unreliability in

cognitive ability measures in the analyses examining job and training performance. In

the analyses examining academic performance, an unrestricted r_{xx} value of .85 was used

to correct for unreliability in cognitive ability measures. When applying the indirect

range restriction procedure, unrestricted applicant r_{xx} values are converted to restricted

incumbent r_{xx} values with the range restriction formula (Hunter, Schmidt, & Le, 2006, p.

604).

Predictor reliabilities were used when making corrections for indirect range

restriction, as well as when calculating true score validities. By definition, operational

validities are not corrected for predictor unreliability. Thus, operational validities

represent true score validities in which predictor unreliability has been reintroduced:

$$\rho_{op} = \rho_{ts} \left(\sqrt{r_{xx}} \right)$$

Criterion Reliability

When criterion measures are unreliable, the observed correlations between

predictors and criteria are attenuated. To address this situation, corrections will be made

for criterion unreliability. Values used to correct for criterion unreliability will vary

according to the specific criteria under investigation.

With regard to academic performance, Kuncel, Credé, and Thomas (2007, p. 59)

note that "unlike typical internal consistency estimates based on a single test administered

at one point in time, estimates are from final grades (typically based on multiple

subevaluations) from multiple raters over the course of months or years." That is,

cumulative grade point averages are expected to be quite reliable since they are based on

multiple ratings (course grades) from multiple raters (instructors). Likewise, single

course grades should be less reliable than cumulative averages based on multiple courses.

Using reliability data from Barritt (1966; r_{yy} = .84), Bendig (1953; r_{yy} = .80), and Reilly

and Warech (1993; r_{yy} = .84), Kuncel et al. (2001) determined the overall mean reliability

of GPAs to be .83 (reliability index = $\sqrt{.83}$ = .91). This reliability value has been used in

a number of subsequent meta-analyses by Kuncel and colleagues (Kuncel et al., 2004;

Kuncel et al., 2005; Kuncel et al., 2007; Kuncel, Wee, Serafin, & Hezlett, 2010) as well

as other scholars (Oh, Schmidt, Shaffer, and Le, 2008). Given the lack of reliability data

presented in primary studies, I adopted Kuncel's r_{yy} estimate of .83 as the reliability estimate for GPA.

Corrections for criterion unreliability were also made when training performance was assessed. In their meta-analysis, Alliger et al. (1997) obtained mean criterion reliabilities of .75 for measures of knowledge-based learning obtained immediately following training ($k = 14$) and .53 for delayed measures of knowledge ($k = 2$). Likewise, they estimated the reliability of learning assessed via behavioral/skill assessments to be .84 ($k = .84$). Unfortunately, Alliger et al. do not report whether their meta-analytic values are CE, CS, inter-rater reliabilities, or some combination thereof. To correct for unreliability in training performance, I adopted the r_{yy} value of .90 adopted by Brown, Le, & Schmidt (2006).

When job performance is the criterion, the appropriate reliabilities to consider are inter-rater reliabilities rather than coefficients of equivalence (such as Cronbach's α) or coefficients of stability. Internal consistency (CE) reliabilities and stability coefficients (CS) fail to account for rater idiosyncrasy (i.e., error specific to the rater). As a result, corrections made using alpha or CS result in substantial underestimates of operational validity. In this study, unreliability in job performance ratings was corrected using the relevant meta-analytic estimates of inter-rater reliability for a single rater reported by Viswesvaran, Ones, and Schmidt (1996). For overall job performance, they report inter-rater reliabilities ranging from .42 for peer ratings to .52 for supervisor ratings.

Range Restriction

When the range of cognitive ability scores is restricted, correlations between cognitive ability and performance will be attenuated. For this reason, range restriction is a form of biased sampling (Sackett & Yang, 2000). To address this bias, it is appropriate to correct for range restriction when estimating operational and true score validities for predicting academic, training, or job performance (or when estimating the corresponding true score correlations between these constructs). Most studies to date have corrected only for direct range restriction (Hunter & Schmidt, 2004). However, in reality, range restriction is almost always indirect, a fact noted by Thorndike (1949) more than half a century ago. Schmidt and his colleagues recently developed a new correction method (Case IV) for indirect range restriction (IRR; e.g., Hunter et al., 2006; Schmidt et al., 2006). This new IRR method was analytically derived (see Hunter et al., 2006 for statistical derivations) and shown to be accurate via extensive Monte-Carlo simulations (Le, 2003; Le & Schmidt, 2006). Previously, many researchers believed that correcting for direct range restriction when indirect range restriction is known to be the case would result in relatively accurate corrections. However, recent research has shown that when range restriction is indirect, correcting for direct range restriction produces considerable underestimates of validity. Schmidt et al. (2008) have shown that this is especially the case for cognitive ability measures. For example, they found that GCA validities corrected for IRR represented validity increases of between 16% and 34% over DRR when predicting job performance and between 8% and 27% over DRR when predicting training performance.

Correlations were corrected for indirect range restriction using the methods presented by Hunter and Schmidt (2004) and described in additional detail by Hunter et

al. (2006). Distributions of u_x values for cognitive ability measures were assembled by extracting the u_x values reported in primary studies or calculating u_x values by comparing the ratio of standard deviations for enrolled students or job incumbents (the restricted population) to the standard deviations reported for normative groups or applicant samples (the unrestricted population). The determination of the appropriate unrestricted reference population is related to particular research question at hand. In the current study, general population norms were used. This offered two key advantages. First, many of the tests included in the data set were traditional measures of cognitive ability with scores reported as deviation IQ's. For such tests, the population mean is 100 with a standard deviation of 15 (16 in the case of the Stanford-Binet). Second, correcting to the population norm allowed college and high school samples to be compared along a common baseline. This helps address the issue of increasing range restriction at higher levels of education. When academic performance was the criterion, the majority of crystallized ability measures utilized were college admissions tests such as the ACT and SAT. These tests are normed to the college applicant population rather than the general population. Given this, for meta-analyses of Gc and academic performance, I corrected for range restriction by applying a weighted composite based on the percentage of high school and college students using the respective high school and college u_x values from the GCA distribution.

When academic performance was the criterion, cognitive ability u_x distributions were constructed by first calculating sample size weighted u_x estimations for high school and college students separately. Next, an overall effective u_x value for the combined sample was estimated by weighting the HS and college u_x values according to the

percentage of high school and college students represented in the overall sample. This is detailed in Table 3.

In some cases utilizing military data (e.g., Brown et al., 2006; Personnel Resonnel Research Board Studies, 1957-1959) researchers reported corrected rather than observed correlations. To prevent overestimation of observed validities when entering this data, I attenuated these correlations using a u_x value of .60. The u_x artifact distributions that were obtained when training and job performance was the criterion are presented in Tables 4 and 5 at the end of this chapter. There was a significant lack of normative values and primary study data necessary to calculate u_x values for Gf measures. Given this, the respective u_x distribution for GCA was used to correct Gf validities for range restriction.

Credibility and Confidence Intervals

It is important to consider the extent to which there is variability in the mean corrected correlations. While zero variability precludes the presence of moderators, large variability suggests that moderators may be operating (Schmidt & Hunter, 1999). Variability around $\bar{\rho}$ is frequently expressed using both credibility and confidence intervals. Credibility intervals are estimates of the distribution of population values (Hunter & Schmidt, 2004; Schmidt & Hunter, 1999; Whitener, 1990). That is, they "provide an estimate of the variability of individual [population] correlations across studies" (Judge & Ilies, 2002, p.800) independent of sampling error. Confidence intervals estimate the variability in the mean correlation due to sampling error rather than the distribution of population correlations (Hunter & Schmidt, 2004; Whitener, 1990).

The width of the confidence interval is determined by the amount of sampling error in the estimate of the mean value. By contrast, credibility intervals are computed after the removal of sampling error. When presenting results for each meta-analysis, I calculated and report the 80% credibility and 95% confidence intervals around each mean corrected correlation ($\bar{\rho}$) using the methodology appropriate for artifact distribution meta-analysis provided by Hunter & Schmidt (2004, p. 207).

Analytic Strategy

At this point I describe how I used the results of the meta-analyses to test the hypotheses presented in Chapter 2. As a reminder, in Chapter 3, I proposed that compared to measures of fluid ability (Gf), crystallized ability measures (Gc) will more strongly predict academic (Hypothesis 1a), training (Hypothesis 1b), and job performance (Hypothesis 1c). Likewise, I also proposed that overall, blended, or GCA measures will be stronger predictors of academic (Hypothesis 2a), vocational training (Hypothesis 2b), and job performance (Hypothesis 2c) than fluid ability (Gf) measures, and equal or stronger predictors of these types of performance than crystallized (Gc) ability measures.

For each meta-analysis, I examined the the 80% credibility intervals to assess whether the mean corrected validities ($\bar{\rho}$ values) are meaningfully different from zero. That is, 80% credibility intervals excluding zero suggest results are generalizable. In this study, credibility intervals are not as important as mean values and the confidence intervals surrounding them. Next, for each criterion of interest, I compared the mean corrected validities obtained for crystallized measures to those obtained for fluid measures (and to the validities for GCA to test hypotheses 2a, 2b, and 2c). Strong

support for my hypotheses is suggested if the validities for Gc measures are greater than the validities for Gf measures and the 95% confidence intervals around the $\bar{\rho}$ values for each type of measure exclude zero and do not overlap. If a small degree of overlap in the 95% confidence intervals is observed, this will indicate some support for my hypotheses. In contrast, if the 95% confidence intervals overlap completely, or to a large degree, this will indicate that the hypotheses are not supported. Likewise, if the validities for Gf measures are greater than the validities for Gc measures and the 95% confidence intervals around the $\bar{\rho}$ values for each type of measure exclude zero and do not overlap, this suggests a pattern of results opposite to that which was hypothesized.

Furthermore, to examine moderators such as level of education, job complexity, and type of test, I also compared the variability around $\bar{\rho}$ values for the moderators to the variability around $\bar{\rho}$ values for the overall sample. When the SD_ρ values are smaller for the moderators, compared to the SD_ρ values at the overall level, this provides evidence of a moderation effect. Likewise, if there is a moderation effect, the 80% credibility intervals for the moderator variables are expected to be narrower than the 80% credibility interval for the overall level.

Table 3. u_x Artifact Distributions for Academic Performance

		General Cognitive Ability		
Category	u_x Method	High School	College	Effective u_x (Total Sample)
Overall	Sample Size Weighted	$u_x = .88$ $SDu_x = .12$ $k = 13$ $N = 1,399$	$u_x = .64$ $SDu_x = .06$ $k = 28$ $N = 7,700$	$u_x = .75$ $k = 110$ $N = 29,739$
High School	Sample Size Weighted	$u_x = .88$ $SDu_x = .12$ $k = 13$ $N = 1,399$	Not Applicable	$u_x = .88$ $k = 32$ $N = 13,290$
College	Sample Size Weighted	Not Applicable	$u_x = .64$ $SDu_x = .06$ $k = 28$ $N = 7,700$	$u_x = .64$ $k = 78$ $N = 16,449$
High Stakes (Overall)	Sample Size Weighted	$u_x = 1.00$ $SDu_x = .06$ $k = 3$ $N = 395$	$u_x = .59$ $SDu_x = .04$ $k = 3$ $N = 496$	$u_x = .83$ $k = 52$ $N = 18,525$

Table 3. Continued

General Cognitive Ability				
Category	u_x Method	High School	College	Effective u_x (Total Sample)
High Stakes (High School)	Sample Size Weighted	$u_x = 1.00$ $SDu_x = .06$ $k = 3$ $N = 395$	Not Applicable	$u_x = 1.00$ $k = 14$ $N = 11,028$
High Stakes (College)	Sample Size Weighted	Not Applicable	$u_x = .59$ $SDu_x = .04$ $k = 3$ $N = 496$	$u_x = .59$ $k = 38$ $N = 7,497$
Low Stakes (Overall)	Sample Size Weighted	$u_x = .83$ $SDu_x = .09$ $k = 9$ $N = 834$	$u_x = .70$ $SDu_x = .08$ $k = 24$ $N = 2,405$	$u_x = .73$ $k = 46$ $N = 4,731$
Low Stakes (High School)	Sample Size Weighted	$u_x = .83$ $SDu_x = .09$ $k = 9$ $N = 834$	Not Applicable	$u_x = .83$ $k = 13$ $N = 1,261$

Table 3. Continued

General Cognitive Ability				
Category	u_x Method	High School	College	Effective u_x (Total Sample)
Low Stakes (College)	Sample Size Weighted	Not Applicable	$u_x = .70$ $SDu_x = .08$ $k = 24$ $N = 2,405$	$u_x = .70$ $k = 33$ $N = 3,470$

Table 4. u_x Artifact Distributions for Training Performance

		Crystallized Ability		
Category	u_x Method	Military Studies (Assumed u_x)	Other Studies (Calculated u_x)	Effective u_x (Total Sample)
Overall	Sample Size Weighted	$u_x = .60$ $SDu_x = .00$ $k = 33$ $N = 22,701$	$u_x = .63$ $SDu_x = .03$ $k = 29$ $N = 3,368$	$u_x = .61$ $k = 114$ $N = 38,793$
Low Complexity	Sample Size Weighted	$u_x = .60$ $SDu_x = .00$ $k = 7$ $N = 5,249$	$u_x = .63$ $SDu_x = .05$ $k = 7$ $N = 393$	$u_x = .61$ $k = 29$ $N = 8,152$
Medium Complexity	Sample Size Weighted	$u_x = .60$ $SDu_x = .00$ $k = 29$ $N = 12,768$	$u_x = .63$ $SDu_x = .02$ $k = 20$ $N = 2,911$	$u_x = .61$ $k = 66$ $N = 22,100$
High Complexity	Sample Size Weighted	No Values	No Values	$u_x = .63$ $k = 4$ $N = 596$

Table 4. Continued

Category	u_x Method	Military Studies (Assumed u_x)	Other Studies (Calculated u_x)	Effective u_x (Total Sample)
Police	Sample Size Weighted	Not Applicable	$u_x = .67$ $SDu_x = .06$ $k = 3$ $N = 965$	$u_x = .67$ $k = 25$ $N = 7,762$
General Cognitive Ability				
Overall	Sample Size Weighted	No Values	$u_x = .60$ $SDu_x = .06$ $k = 10$ $N = 4,144$	$u_x = .60$ $k = 24$ $N = 7,563$
Low Complexity	Sample Size Weighted	No Values	No Values	$u_x = .60$ $k = 2$ $N = 156$
Medium Complexity	Sample Size Weighted	No Values	$u_x = .66$ $SDu_x = .08$ $k = 8$ $N = 1,320$	$u_x = .66$ $k = 14$ $N = 2,581$

Table 4. Continued

Category	u_x Method	Military Studies (Assumed u_x)	Other Studies (Calculated u_x)	Effective u_x (Total Sample)
High Complexity	Sample Size Weighted	No Values	$u_x = .57$ $SDu_x = .03$ $k = 2$ $N = 2,824$	$u_x = .57$ $k = 2$ $N = 2,824$
Police	Sample Size Weighted	Not Applicable	$u_x = .65$ $SDu_x = .09$ $k = 4$ $N = 1,011$	$u_x = .65$ $k = 10$ $N = 2,272$

Table 5. u_x Artifact Distributions for Job Performance

Crystallized Ability				
Category	u_x Method	Military Studies (Assumed u_x)	Other Studies (Calculated u_x)	Effective u_x (Total Sample)
Overall	Sample Size Weighted	$u_x = .60$ $SDu_x = .00$ $k = 17$ $N = 3,312$	$u_x = .74$ $SDu_x = .06$ $k = 135$ $N = 10,776$	$u_x = .71$ $k = 199$ $N = 18,619$
Low Complexity	Sample Size Weighted	$u_x = .60$ $SDu_x = .00$ $k = 5$ $N = 1,370$	$u_x = .76$ $SDu_x = .05$ $k = 77$ $N = 5,759$	$u_x = .74$ $k = 108$ $N = 9,307$
Medium Complexity	Sample Size Weighted	$u_x = .60$ $SDu_x = .00$ $k = 12$ $N = 1,942$	$u_x = .72$ $SDu_x = .07$ $k = 37$ $N = 3,247$	$u_x = .68$ $k = 58$ $N = 6,603$
High Complexity	Sample Size Weighted	No Values	$u_x = .70$ $SDu_x = .05$ $k = 21$ $N = 1,770$	$u_x = .69$ $k = 27$ $N = 2,214$

Table 5. Continued

General Cognitive Ability				
Category	u_x Method	Military Studies (Assumed u_x)	Other Studies (Calculated u_x)	Effective u_x (Total Sample)
Overall	Sample Size Weighted	No Values	$u_x = .78$ $SDu_x = .09$ $k = 27$ $N = 3{,}088$	$u_x = .78$ $k = 86$ $N = 8{,}070$
Low Complexity	Sample Size Weighted	No Values	$u_x = .80$ $SDu_x = .05$ $k = 14$ $N = 1{,}581$	$u_x = .80$ $k = 37$ $N = 3{,}420$
Medium Complexity	Sample Size Weighted	No Values	$u_x = .75$ $SDu_x = .02$ $k = 8$ $N = 736$	$u_x = .75$ $k = 31$ $N = 2{,}456$
High Complexity	Sample Size Weighted	No Values	$u_x = .70$ $SDu_x = .16$ $k = 4$ $N = 462$	$u_x = .70$ $k = 11$ $N = 861$

Table 5. Continued

General Cognitive Ability				
Category	u_x Method	Military Studies (Assumed u_x)	Other Studies (Calculated u_x)	Effective u_x (Total Sample)
OCB	Sample Size Weighted	No Values	$u_x = .80$ $SDu_x = .05$ $k = 7$ $N = 871$	$u_x = .80$ $k = 7$ $N = 871$

CHAPTER 5

RESULTS

Chapter Overview

In this chapter I present the results of the meta-analyses conducted to test the hypotheses proposed in Chapter 3. Given that the primary objective of my study is to examine the relative differences in predictive validity between fluid and crystallized ability, I focus the presentation of results on this issue. I begin by presenting the results for academic performance, proceed to training performance, and then conclude by presenting the results for job performance. Within each of these criteria, I first present the results for fluid ability, as it serves as the comparative reference point for each of the hypotheses. I follow this by presenting the results for crystallized ability and general cognitive ability. When testing each hypothesis, I utilized the analytic strategy described in Chapter 4.

Notation

Some readers may be unfamiliar with meta-analysis and the notation used for presenting meta-analytic results. Others may be familiar with meta-analysis, but accustomed to a different notation system. Accordingly, I provide a brief summary of the specific notation used within this chapter as well as the results tables which follow:

- k –the number of independent (correlations) samples that contributed to each meta-analysis;

- N – the total sample size;

- r_{obs} - the sample-size weighted mean observed correlation between cognitive ability and the performance criterion of interest;

- SD_r – the standard deviation of the sample-size weighted mean observed correlation;

- ρ_{op} – the mean operational validity. This is the mean observed validity after it has been corrected for indirect range restriction in the predictor and measurement error in the criterion. Operational validities are sometimes referred to as "true" validities;

- $SD\rho_{op}$ - the standard deviation of the $\rho_{op;}$

- 80% CrI – 80% Credibility Interval, a measure of variability in the distribution of population correlations. Credibility intervals are used to test for generalizability. Results are assumed to be generalizable when this interval excludes zero. Credibility intervals are computed after removal of sampling error;

- 95% CI – 95% Confidence interval; Confidence intervals estimate the variability due to sampling error in the mean correlation rather than the entire distribution of correlations;

- ρ_{ts} – the true score correlation. This is the mean observed correlation after it has been corrected for indirect range restriction in the predictor and measurement error in both the criterion and predictor. True score correlations are an indication of the construct-level relationship between two variables (in this study, the construct-level relationship between cognitive ability and performance). Given that study is primarily concerned with the differential

validities of Gf, Gc, and GCA for predicting real-world performance, true

score correlations are not the focus of this chapter. Nevertheless, these

validities are presented in each of the results tables which follow;

- $SD\rho_{ts}$ – the standard deviation of the true score correlation.

Cognitive Ability and
Academic Performance

Fluid Ability and
Academic Performance

Results for the meta-analyses examining fluid ability and academic performance

are presented in Table 6. The overall observed validity of Gf for predicting academic

performance is .26 (SD = .14). After corrections were made for indirect range restriction

and criterion unreliability, the correlation increased to .40 ($SD\rho_{op}$ = .14). The 80%

credibility interval excluded zero, indicating the results are generalizable. That is, we can

say that there is a positive relationship between fluid ability and academic performance.

Although the observed validity for Gf was stronger for high school samples (r = .30)

compared to college samples (r = .22), the operational validities are closer in magnitude

(HS ρ_{op} = .38, College ρ_{op}=.44). However, there was considerable overlap in both the

80% credibility intervals and 95% confidence intervals for the high school and college

samples. This finding suggests that the validity of Gf is similar at both educational

levels.

Although many associate fluid ability exclusively with traditional tests such as

Raven's Standard or Advanced Progressive Matrices, or with Cattell's Culture Fair

Intelligence Test (CFIT), my data set reveals that researchers also measure fluid ability

using a number of other scales. Given this, moderator analyses were performed to

examine the possibility that these tests vary in their predictive power (which in turn might

also suggest that these scales are in fact measuring different underlying constructs). The

D-48 (a nonverbal, Gf-loaded test based on domino series) and tests of abstract or

inductive reasoning share similar operational validities (ρ_{op} = .46 and .44 respectively),

with both displaying a higher operational validity than traditional tests such as Raven's

Progressive Matrices or Cattell's Culture Fair Intelligence Test (CFIT) (ρ_{op} = .37).

However, there is considerable overlap between tests with regard to both the 80%

credibility intervals and 95% confidence intervals.

It is interesting to note the relatively large $SD\rho_{op}$ (.20) for traditional Gf tests

administered to college students. This variability may be due in part to the fact that some

samples were administered Standard versions of the test while others were given

Advanced versions. McLaurin and Farrar (1973) have noted that the Standard

Progressive Matrices are too simplistic to be of use within most college samples. They

observed notably higher correlations when using the Advanced version of the Raven's.

However, when considering abstract and inductive reasoning tests, variability was greater

within high school ($SD\rho_{op}$ = .18) vs. college samples ($SD\rho_{op}$ = .10).

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Crystallized Ability and
Academic Performance

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The results for crystallized ability and academic performance are presented in

Table 7. The observed validity of crystallized ability for predicting academic

performance is .36 (SD = .09). After corrections for indirect range restriction and

criterion unreliability were made, the correlation increased to .65 ($SD\rho_{op}$ = .10). These

validity estimates are based on a large number of independent correlations ($k = 157$) as well as a large total sample size ($N = 199,642$). The sample size is largely due to the inclusion of a study conducted by Sackett et al. (2009). In this study, Sackett and colleagues presented SAT validity data for over 150,000 students from multiple colleges and universities in the United States ($k = 41$). Given the very large sample size of this single study, I calculated results both including and excluding the study data. Both sets of validities are reported in Table 7. When the data from this study was excluded, the observed validity increased to .41 ($SD = .12$) and the operational validity increased to .69, however the pattern of relationships remains consistent regardless of whether or not the data is included. In discussing the results for Gc, I refer to the results which *include* the Sackett et al. data unless otherwise noted. Analyses at the high school level did not contain any data from the Sackett et al. study.

The operational validity of Gc for predicting academic performance is large and positive in both the high school ($\rho_{op} = .53$, $SD\rho_{op} = .17$) and college subgroups ($\rho_{op} = .65$, $SD\rho_{op} = .10$). For all levels of analysis, the 80% credibility intervals excluded zero indicating that the results are generalizable. When comparing the validities of Gc to those of Gf, it is clear that Gc measures are stronger predictors of academic performance. This is true at the overall ($\rho_{op} = .65$ for Gc vs. .40 for Gf), high school ($\rho_{op} = .53$ for Gc vs. .38 for Gf), and college levels ($\rho_{op} = .65$ for Gc vs. .44 for Gf). Furthermore, there is no overlap in the 95% confidence intervals for the overall and college levels. Only the end-point (.01) of the 95% CI's overlap for the high school samples (95% CI for Gc = .44 - .63 vs. 95% CI for Gf = .33-.44). Taken together, these results provide support for Hypothesis 1a.

General Cognitive Ability
and Academic Performance

The results for General Cognitive Ability (GCA) and academic performance are

presented in Table 8. The observed validities of GCA are .47 at the overall level, .53 at

the high school level, and .42 at the college level. After corrections for indirect range

restriction and criterion unreliability were made, the correlations increased to .68 at the

overall level ($SD\rho_{op}$ = .06), .65 at the high school level ($SD\rho_{op}$ = .05), and .72 at the

college level ($SD\rho_{op}$ = .08). The standard deviations surrounding ρ_{op} were small, despite

the fact that data was collected from a wide variety of countries, settings, and time

periods. This offers support for the notion that GCA is a robust and stable predictor of

academic performance.

It is interesting to note that the mean operational validity of GCA for predicting

academic performance in college (ρ_{op} = .72, 95% CI = .68 - .76) is higher than that of

GCA for predicting academic performance in high school (ρ_{op} = .65, 95% CI = .63 - .68),

with only the end points of the 95% confidence intervals overlapping. Similar results are

also evident for crystallized ability (College ρ_{op} = .65, 95% CI = .63 - .68 vs. HS College

ρ_{op} = .53, 95% CI = .44 - .63).   These results appear contrary to most previous research

which has found that the validity of cognitive ability decreases as the level of education

increases. Consistent with previous research, the observed validities for Gc and GCA

were indeed lower for college students. However, unlike most previous studies, range

restriction corrections in the current study were based on population level norms (i.e.,

Mean IQ = 100, SD = 15) rather than norms specific to high school or college students.

This use of a common baseline has the effect of controlling for differences in range

restriction between the two levels of education. The higher operational validities for college students that were found after correcting for range restriction may reflect the increased cognitive demands of college coursework.

As hypothesized (Hypothesis 2a), the operational validities of GCA were higher than those for Gf at all levels of analysis: .68 vs. .40 for the overall samples, .65 vs. .38 for the high school samples, and .72 vs. .44 for the college samples. Furthermore, there was no overlap between the 95% confidence intervals, suggesting these are indeed true differences in validity. When comparing the operational validities of GCA to Gc, the validities were similar in magnitude for the overall and college samples, and there was considerable overlap between the 95% confidence intervals. In HS samples GCA displayed a higher validity than Gc (ρ_{op} =.65 vs. .53), with only the endpoint of the 95% confidence intervals overlapping (95% CI = .63 - 68 for GCA vs. .44 - .63 for Gc). Taken together, these results provide strong support for Hypothesis 2a.

High Stakes vs. Low Stakes Testing

All of the studies that assessed fluid ability and academic performance were conducted for low stakes research purposes, thus a comparison between high and low stakes testing situations was not possible for Gf measures. However, the data set did permit the analysis of high stakes vs. low stakes testing for academic samples that utilized crystallized and general cognitive ability measures.

Hypothesis 3a proposed that for high school students, cognitive ability tests would demonstrate higher observed validities under low stakes testing conditions. This hypothesis was supported for Gc measures. The observed validities of Gc are .48 ($k = 9$, $N = 953$) under low stakes testing conditions and .40 ($k = 9$, $N = 1147$) under high stakes

testing conditions. Some caution should be exercised in interpreting this finding given the small total sample sizes. Further, due to data limitations, range restriction estimates were not available for Gc measures at the high school level. Thus, it was not possible to determine whether high stakes samples were more restricted (i.e., demonstrated less variability in test scores) than low stakes samples. Hypothesis 3a was not supported for GCA measures. The observed validity of GCA tests was .53 in both samples (High Stakes: $k = 14$, $N = 11,028$; Low Stakes: $k = 13$, $N = 1,261$). Again, caution should be advised in interpreting this result given the relatively small total sample size for low stakes GCA tests. In addition, contrary to what was expected, the mean sample size weighted u_x value was higher for high stakes GCA tests (mean $u_x = 1.00$, $SD = .06$, $k = 3$, $N = 395$) compared to low stakes GCA tests (mean $u_x = .83$, $SD = .09$, $k = 9$, $N = 834$). However, the mean u_x value for high stakes tests was based on only three studies with a combined sample size of 395 students. This is significantly smaller than the overall 14 studies with a combined sample size of 11,028 students. Therefore, the obtained u_x value may not be representative of the entire high stakes GCA high school sample.

Hypothesis 3b proposed that the observed validities of cognitive ability tests for college students would be similar under high and low stakes testing conditions. This hypothesis was supported for Gc measures. The observed validity for Gc tests was .41 under high stakes conditions (.36 including the Sackett et al., 2009 data) and .40 under low stakes conditions (the low stakes samples did not include any data from Sackett et al.). With regard to GCA measures administered in college samples, as expected, u_x values were smaller for high stakes samples (mean $u_x = .59$, $SD = .04$, $k = 3$, $N = 496$) compared to low stakes samples (mean $u_x = .70$, $SD = .08$, $k = 24$, $N = 2,405$). However,

contrary to Hypothesis 3b, the mean observed validity of GCA measures administered

under high stakes conditions ($r = .47$) was higher than the mean observed validity of

GCA measures given under low stakes conditions ($r = .31$).

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Cognitive Ability
and Training Performance

Fluid Ability
and Training Performance

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Table 9 presents the results for the meta-analyses examining the relationship

between fluid ability and training performance. At the overall level, the observed validity

of Gf is .25. This validity increases to .54 ($SD\rho_{op} = .17$) when corrections for indirect

range restriction and criterion unreliability are made. Likewise, the 80% credibility

intervals exclude zero, an indication that the results are generalizable. The mean

operational validity of Gf for predicting training performance in high complexity jobs

($\rho_{op} = .67$) is greater than that for medium complexity jobs, ($.\rho_{op} = .44$). However, a

closer inspection reveals there is substantial overlap between the 95% confidence

intervals (95% CI for medium complexity jobs = .32 to .56 for medium complexity jobs

vs. .36 to .97 for high complexity jobs), suggesting the validities are similar in

magnitude. There were no low complexity jobs in the Gf – training performance sample.

Taken together, these findings provide support for Hypothesis 4a. Further, when training

performance is the criterion, the operational validities of Gf are similar for traditional

fluid measures such as Raven's Progressive Matrices and the Culture Fair Intelligence

Test ($\rho_{op} = .51$, $SD\rho_{op} = .23$, 95% CI = .27 - .74) compared to measures of abstract or

inductive reasoning ($\rho_{op} = .56$, $SD\rho_{op} = .14$, 95% CI = .43 - .69).

Crystallized Ability
and Training Performance

Table 10 presents the results for the meta-analyses examining crystallized ability

and training performance. Gc measures were strong, positive predictors of training

performance. When all jobs are considered together, the observed validity of crystallized

ability for predicting training performance is .38. This validity increases to .70 ($SD\rho_{op}$ =

.14) after corrections for indirect range restriction and criterion unreliability are made.

Likewise, the 80% credibility intervals exclude zero, an indication that the results are

generalizable. Operational validity estimates at the overall level were based on a large

number of independent samples (k = 114) and a relatively large total sample size (N = 38,

793). Further, the operational validities of Gc are strong and positive at all levels of job

complexity, with 80% credibility intervals excluding zero: .73 for low complexity jobs,

.74 for medium complexity jobs, and .75 for high complexity jobs. Although the mean

validity values do increase with complexity, the 95% confidence intervals overlap

considerably suggesting the validities are effectively the same at all levels of complexity.

This finding provides support for Hypothesis 4a.

Although both fluid and crystallized measures were positively related to training

performance, Gc measures are stronger predictors of performance at the overall level (ρ_{op}

= .70 for Gc vs. .54 for Gf), as well as for medium complexity jobs (ρ_{op} = .74 for Gc vs.

.44 for Gf). Further, at the overall level only the end points (.01) of the 95% confidence

intervals overlap (95% CI = .66 - .75 for Gc vs. .42 - .66 for Gf). For medium complexity

jobs, the 95% confidence intervals surrounding ρ_{op} do not overlap. Taken together, these

results offer support for Hypothesis 1b.

For high complexity jobs, the mean operational validity is higher for Gc measures (ρ_{op} = .75; 95% CI = .59 - .92) compared to Gf measures (ρ_{op} = .67; 95% CI = .36 - .97). However, the 95% confidence intervals overlap completely, indicating that it is not possible to conclude that the validities for Gc and Gf differ meaningfully for predicting training performance in high complexity jobs. Caution is warranted in interpreting results at high complexity levels given that the k's and N's are quite small for both Gf (k = 5, N = 569) and Gc (k = 4, N = 596).

Nearly 25% of the studies in the data set examined the relationship between cognitive ability and training performance in police academies (these are typically long-term training programs ranging from 12 to 24 weeks in duration). This allowed comparisons to be made between the validities of Gf and Gc for predicting training performance within a single occupation. In this regard, the mean operational validity of Gc measures (.66) for predicting police training performance was higher than that of Gf measures (.45). However, there was overlap between the 95% confidence intervals for these measures (95% CI = .58 - .74 for Gc vs. .20 - .70 for Gf). The wider confidence intervals for Gf are largely the function of the small number of independent samples (k = 5) contributing to this analysis. In contrast, operational validity estimates for Gc and police training performance were based on a larger number of independent correlations as well as a larger total sample size (k = 25, N = 7,762).

General Cognitive Ability
and Training Performance

Table 11 presents the results for the meta-analyses examining general cognitive ability and training performance. Compared to the results for Gc measures ($k = 114$), a surprisingly small number of independent samples ($k = 24$) examined general cognitive ability and training performance. While this may be a function of the current data set, the disparity may also be due to the fact that previous meta-analyses have likely classified tests such as the General Aptitude Test Battery (GATB) or Armed Forces Vocational Aptitude Battery (ASVAB) as measures of GCA. In contrast, in the current study, verbal and quantitative scores from these test batteries were combined to estimate crystallized ability.

At the overall level, the observed validity of GCA for predicting training performance is .28. This validity increases to .59 ($SD\rho_{op} = .15$) after corrections for indirect range restriction and criterion unreliability are made. The 80% credibility intervals exclude zero at all levels of analysis, suggesting validities for GCA and training performance are generalizable. The operational validities of GCA were strong and positive for low (.53), medium (.56), and high (.57) complexity jobs. However, there was considerable overlap in the 95% confidence intervals between complexity levels. This finding is consistent with previous research (Hunter, 1980; Hunter & Hunter, 1984) as well as Hypothesis 4a, which proposed that cognitive test validities would be similar across job complexity levels. However, the results for GCA and training performance for low complexity jobs and high complexity jobs are both based on only 2 independent

samples each (compared with 14 for medium complexity jobs). This makes a meaningful

test of Hypothesis 4a prohibitive with regard to GCA.

Compared to Gf, the mean operational validity of GCA was stronger for

predicting training performance in medium complexity jobs (ρ_{op} = .56 for GCA vs. .44

for Gf). However, there was some overlap in the 95% confidence intervals for these two

types of measures (95% CI for GCA = .42 - .70; 95% CI for Gf = .32 - .56). On average,

the validities of GCA for predicting training performance were smaller than those of Gc,

with only minor overlap of the 95% confidence intervals. This finding lies in contrast to

the pattern of validities hypothesized by Hypothesis 2c. Nevertheless, the operational

validities for both types of measures are strong and positive, suggesting these are both

good predictors of training performance.

<u>Cognitive Ability</u>
<u>and Job Performance</u>

Fluid Ability
and Job Performance

Table 12 presents the results for fluid ability and job performance. The observed

validity of Gf measures for predicting job performance is .14 with a large standard

deviation (SD_r = .17). The validity of Gf increased to .27 ($SD\rho_{op}$ = .26) after correcting

for indirect range restriction and criterion unreliability. However, the 80% credibility

interval included zero, indicating that the results are not generalizable at the overall level.

At low levels of job complexity, the operational of Gf was found to be -.01, and the

credibility intervals included zero (80% CrI = -.49 - .46), suggesting that the results are

not generalizable. However, it is important to note that this analysis was based on only

two samples with a combined N of 251. Given this, caution should be used when interpreting this result. A result in the opposite direction was found at high levels of job complexity (ρ_{op} = 0.64, $SD\rho_{op}$ = .10; 80 CrI = .52 − .77). Again, caution is warranted in interpreting this result given that it is based on only two samples (both computer programmers who were administered the Abstract Reasoning scale of the Differential Aptitude Tests) with a combined sample size of only 132. The operational validity of Gf for medium complexity jobs is .26 ($SD\rho_{op}$ = .19) with the 80% credibility interval excluded zero. Within medium complexity jobs, inductive and abstract reasoning measures displayed a higher operational validity than traditional Gf measures such as the Raven's and CFIT (.31 vs. .20). However, there was overlap between the 95% confidence intervals. Thus, it is not possible to say that one measure is superior to the other for predicting job performance. Taken together, these results indicate that Gf validities for predicting job performance vary widely.

<div align="center">

Crystallized Ability
and Job Performance

</div>

The results for crystallized ability and job performance are presented in Table 13. In contrast to Gf measures, Gc measures were stronger and less varied predictors of job performance. At the overall level, the operational validity of Gc was .49 ($SD\rho_{op}$ = .15). 80% credibility intervals excluded zero at all levels of analysis, suggesting the results are generalizable. Gc measures also demonstrated the previously observed pattern whereby validities increase as the level of job complexity increases: the operational validity of Gc was .45 for low complexity jobs, .54 for medium complexity jobs, and .59 for high complexity jobs. This offers support for Hypothesis 4b.

When compared directly with the operational validities of Gf measures, the validity for Gc measures was higher for the overall sample of jobs (.49 vs. .29), for low complexity jobs (.45 vs. -.01), and for medium complexity jobs (.48 vs. .26) with no overlap between the 95% confidence intervals. Again caution should be used when interpreting the comparison for low level jobs since the Gf analysis only included two samples. For high complexity jobs, the mean operational validity of Gc was similar to but slightly smaller than Gf (.59 vs. .64), with complete overlap between the 95% confidence intervals. Again, caution should be used when interpreting this result since the Gf analysis was based on only two samples of a single job (computer programmers). It is possible this high validity is a unique characteristic of the computer programmer job, and it is likely that Gc tests would also display very high validities for computer programmers. In this regard, Schmidt, Gast-Rosenberg, and Hunter (1980) conducted a validity generalization study for computer programmer jobs. They found that a battery of cognitive tests (number series, figural analogies, and arithmetic reasoning) displayed mean operational validities of .71 for job performance and .91 for training performance.

Taken as a whole, these results suggest that compared with Gf measures, Gc measures are better predictors of job performance for low and medium complexity jobs. These findings provide support for Hypothesis 1c.

General Cognitive Ability
and Job Performance

Table 14 presents the meta-analytic results for General Cognitive Ability and job performance. As was the case with academic performance, GCA was a strong and positive predictor of job performance. Considering all jobs and samples together at the

overall level of analysis, the observed validity of GCA is .23. After correcting for range restriction and criterion unreliability, the correlation increased to .43 ($SD\rho_{op}$ = .15). 80% credibility intervals excluded zero at all levels of analysis, suggesting the results are generalizable. GCA measures also demonstrated the previously observed pattern whereby validities increase as the level of job complexity increases: the operational validity of GCA was .37 for low complexity jobs, .48 for medium complexity jobs, and .60 for high complexity jobs.   This provides additional support for Hypothesis 4b.

When compared directly with Gf measures, GCA measures were higher for the overall sample of jobs (.43 vs. .29), for low complexity jobs (.37 vs. -.01), and for medium complexity jobs (.48 vs. .26) with no overlap between the 95% confidence intervals. As noted above, caution should be used when interpreting the comparison for low level jobs since the Gf analysis only included two samples. For high complexity jobs, the mean operational validity of GCA was similar to but slightly smaller than Gf (.60 vs. .64); however, there was complete overlap between the 95% confidence intervals. Again, caution should be used when interpreting this result since the Gf analysis was based on only two samples of a single job (computer programmers). Finally, a small number of studies (k = 7, N= 871) reported relationships between GCA and organizational citizenship behaviors. The operational validity of GCA for predicting OCB's was .18 ($SD\rho_{op}$ = .11), with the 80% credibility interval excluding zero. Taken together, these results provide support for Hypothesis 2c.

Table 6. Fluid Ability (Gf) and Academic Performance

Predictor/Test	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(8)		(9)	(10)
							80% CrI		95% CI			
	k	N	r_{obs}	SD_r	ρ_{op}	$SD\rho_{op}$	LL	UL	LL	UL	ρ_{ts}	$SD\rho_{ts}$
Validity of Fluid Ability by Educational Level												
Overall	67	7,991	0.26	0.14	0.40	0.14	0.22	0.58	0.35	0.45	0.43	0.15
High School	26	4,134	0.30	0.13	0.38	0.13	0.21	0.55	0.32	0.44	0.41	0.14
College	41	3,857	0.22	0.14	0.44	0.17	0.23	0.65	0.36	0.53	0.48	0.18
Validity of Fluid Ability by Scale Type												
Traditional *Gf* Measures (Raven's & Culture Fair)	32	4,658	0.25	0.13	0.37	0.13	0.20	0.53	0.30	0.43	0.40	0.14
High School	12	3,094	0.28	0.10	0.36	0.10	0.24	0.49	0.29	0.44	0.39	0.11
College	20	1,564	0.19	0.16	0.38	0.20	0.12	0.63	0.24	0.52	0.41	0.22
D-48 (Dominoes Test)	14	1,159	0.27	0.14	0.46	0.11	0.32	0.60	0.33	0.58	0.50	0.12
High School	4	341	0.25	0.16	0.32	0.15	0.13	0.51	0.12	0.52	0.35	0.16
College	10	818	0.27	0.13	0.54	0.11	0.39	0.68	0.38	0.69	0.58	0.12

Table 6. Continued

Predictor/Test	(1)	(2)	(3)	(4)	(5)	(6)	(7) 80% CrI		(8) 95% CI		(9)	(10)
	k	N	r_{obs}	SD_r	ρ_{op}	$SD\rho_{op}$	LL	UL	LL	UL	ρ_{ts}	$SD\rho_{ts}$
Abstract & Inductive Reasoning	24	2,471	0.26	0.15	0.44	0.17	0.23	0.66	0.34	0.55	0.48	0.18
High School	10	699	0.39	0.18	0.48	0.18	0.26	0.71	0.34	0.62	0.52	0.19
College	14	1,772	0.21	0.10	0.44	0.10	0.31	0.57	0.33	0.55	0.48	0.11

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion <u>and</u> predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 7. Crystallized Ability (Gc) and Academic Performance

Predictor/Test	(1) k	(2) N	(3) r_{obs}	(4) SD_r	(5) ρ_{op}	(6) $SD\rho_{op}$	(7) 80% CrI LL	(7) 80% CrI UL	(8) 95% CI LL	(8) 95% CI UL	(9) ρ_{ts}	(10) $SD\rho_{ts}$
Validity of Crystallized Ability by Educational Level												
Overall	157	199,642	0.36	0.09	0.65	0.10	0.53	0.78	0.63	0.68	0.71	0.11
Excluding Sackett et al. (1999)	116	31,936	0.41	0.12	0.69	0.11	0.55	0.82	0.65	0.72	0.74	0.12
High School	18	2,100	0.43	0.17	0.53	0.17	0.32	0.75	0.44	0.63	0.58	0.18
College	139	197,542	0.36	0.08	0.65	0.10	0.53	0.78	0.63	0.68	0.71	0.11
Excluding Sackett et al. (1999)	98	29,836	0.41	0.11	0.70	0.11	0.56	0.84	0.66	0.74	0.76	0.12
Validity of Crystallized Ability by Testing Purpose and Educational Level												
High Stakes Testing (Selection & Assessment)	133	196,746	0.36	0.08	0.71	0.09	0.60	0.83	0.69	0.74	0.77	0.10
Excluding Sackett et al.(1999)	92	29,040	0.41	0.11	0.74	0.09	0.62	0.86	0.70	0.78	0.81	0.10
High School	9	1,147	0.40	0.21	0.44	0.21	0.17	0.70	0.29	0.58	0.47	0.23
College	124	195,599	0.36	0.08	0.71	0.09	0.60	0.83	0.69	0.74	0.78	0.10
Excluding Sackett et al. (1999)	83	27,893	0.41	0.11	0.76	0.09	0.65	0.87	0.72	0.80	0.83	0.10

Table 7. Continued

Predictor/Test	(1)	(2)	(3)	(4)	(5)	(6)	(7) 80% CrI		(8) 95% CI		(9)	(10)
	k	N	r_{obs}	SD_r	ρ_{op}	$SD\rho_{op}$	LL	UL	LL	UL	ρ_{ts}	$SD\rho_{ts}$
Low Stakes Testing (Research)	16	1,950	0.44	0.12	0.63	0.09	0.51	0.75	0.54	0.71	0.68	0.10
High School	9	953	0.48	0.08	0.62	0.04	0.58	0.67	0.55	0.69	0.68	0.04
College	7	997	0.40	0.13	0.63	0.13	0.47	0.80	0.48	0.79	0.68	0.14

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion <u>and</u> predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 8. General Cognitive Ability (GCA) and Academic Performance

Predictor/Test	(1) k	(2) N	(3) r_{obs}	(4) SD_r	(5) ρ_{op}	(6) $SD\rho_{op}$	(7) 80% CrI LL	(7) 80% CrI UL	(8) 95% CI LL	(8) 95% CI UL	(9) ρ_{ts}	(10) $SD\rho_{ts}$
Validity of General Cognitive Ability by Educational Level												
Overall	110	29,739	0.47	0.10	0.68	0.06	0.60	0.76	0.65	0.71	0.74	0.07
High School	32	13,290	0.53	0.06	0.65	0.05	0.59	0.72	0.63	0.68	0.71	0.06
College	78	16,449	0.42	0.10	0.72	0.08	0.62	0.82	0.68	0.76	0.78	0.09
Validity of General Cognitive Ability by Testing Purpose and Educational Level												
High Stakes Testing (Selection & Assessment)	52	18,525	0.51	0.07	0.66	0.00	0.66	0.66	0.63	0.68	0.71	0.00
High School	14	11,028	0.53	0.05	0.58	0.04	0.53	0.64	0.55	0.61	0.63	0.05
College	38	7,497	0.47	0.08	0.82	0.04	0.77	0.87	0.77	0.86	0.89	0.04
Low Stakes Testing (Research)	46	4,731	0.37	0.14	0.57	0.14	0.39	0.75	0.51	0.63	0.62	0.15
High School	13	1,261	0.53	0.11	0.68	0.09	0.57	0.79	0.60	0.76	0.74	0.09
College	33	3,470	0.31	0.11	0.53	0.08	0.44	0.63	0.47	0.59	0.58	0.08

Table 8. Continued

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion and predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 9. Fluid Ability (Gf) and Training Performance

Predictor/Test	(1) k	(2) N	(3) r_{obs}	(4) SD_r	(5) ρ_{op}	(6) $SD\rho_{op}$	(7) 80% CrI		(8) 95% CI		(9) ρ_{ts}	(10) $SD\rho_{ts}$
							LL	UL	LL	UL		
Validity of Fluid Ability by Level of Job Complexity												
Overall	20	3,724	0.25	0.13	0.54	0.17	0.32	0.76	0.42	0.66	0.59	0.19
Medium (Job Zone 3)	11	2,658	0.23	0.11	0.44	0.15	0.25	0.63	0.32	0.56	0.48	0.16
Police	5	740	0.24	0.15	0.45	0.20	0.19	0.71	0.20	0.70	0.49	0.22
High (Job Zones 4 & 5)	5	569	0.32	0.16	0.67	0.19	0.42	0.91	0.36	0.97	0.73	0.21
Validity of Fluid Ability by Scale Type and Level of Job Complexity												
Traditional *Gf* Measures (Raven's, Culture Fair, & IPAT-G)	7	1,283	0.23	0.15	0.51	0.23	0.21	0.80	0.27	0.74	0.55	0.25
Abstract/Inductive Reasoning, & Other Measures	13	2,441	0.25	0.11	0.56	0.14	0.38	0.74	0.43	0.69	0.61	0.15

Table 9. Continued

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion and predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 10. Crystallized Ability (Gc) and Training Performance

Predictor/Test	(1) k	(2) N	(3) r_{obs}	(4) SD_r	(5) ρ_{op}	(6) $SD\rho_{op}$	(7) 80% CrI		(8) 95% CI		(9) ρ_{ts}	(10) $SD\rho_{ts}$
							LL	UL	LL	UL		
Validity of Crystallized Ability by Level of Job Complexity												
Overall	114	38,793	0.38	0.13	0.70	0.14	0.53	0.88	0.66	0.75	0.77	0.15
Low (Job Zones 1 & 2)	29	8,152	0.41	0.12	0.73	0.11	0.59	0.88	0.65	0.81	0.80	0.12
Medium (Job Zone 3)	66	22,100	0.42	0.12	0.74	0.11	0.60	0.88	0.69	0.79	0.81	0.12
Police	25	7,762	0.41	0.13	0.66	0.13	0.49	0.83	0.58	0.74	0.72	0.15
High (Job Zones 4 & 5)	4	596	0.45	0.10	0.75	0.07	0.67	0.84	0.59	0.92	0.83	0.07

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion <u>and</u> predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 11. General Cognitive Ability (GCA) and Training Performance

Predictor/Test	(1) k	(2) N	(3) r_{obs}	(4) SD_r	(5) ρ_{op}	(6) $SD\rho_{op}$	(7) 80% CrI		(8) 95% CI		(9) ρ_{ts}	(10) $SD\rho_{ts}$
							LL	UL	LL	UL		
Validity of General Cognitive Ability by Level of Job Complexity												
Overall	24	7,563	0.28	0.11	0.59	0.15	0.39	0.78	0.49	0.68	0.64	0.17
Low (Job Zones 1 & 2)	2	156	0.22	0.00	0.53	0.00	0.53	0.53	0.53	0.53	0.58	0.00
Medium (Job Zone 3)	14	2,581	0.32	0.16	0.56	0.19	0.31	0.81	0.42	0.70	0.61	0.21
Police	10	2,272	0.31	0.16	0.55	0.21	0.28	0.82	0.37	0.72	0.60	0.23
High (Job Zones 4 & 5)	2	2,824	0.22	0.06	0.57	0.10	0.44	0.70	0.34	0.79	0.62	0.11

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion <u>and</u> predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 12. Fluid Ability (Gf) and Job Performance

Predictor/Test	(1)	(2)	(3)	(4)	(5)	(6)	(7) 80% CrI		(8) 95% CI		(9)	(10)
	k	N	r_{obs}	SD_r	ρ_{op}	$SD\rho_{op}$	LL	UL	LL	UL	ρ_{ts}	$SD\rho_{ts}$
Validity of Fluid Ability by Level of Job Complexity												
Overall	23	3,273	0.14	0.17	0.27	0.26	-0.07	0.60	0.14	0.39	0.29	0.28
Low (Job Zones 1 & 2)	2	251	-0.01	0.23	-0.01	0.37	-0.49	0.46	-0.57	0.54	-0.02	0.40
Medium (Job Zone 3)	10	1,677	0.12	0.12	0.26	0.19	0.02	0.49	0.10	0.41	0.28	0.20
High (Job Zones 4 & 5)	2	132	0.31	0.13	0.64	0.10	0.52	0.77	0.27	1.02	0.71	0.11
Validity of Fluid Ability by Scale Type and Level of Job Complexity												
Traditional *Gf* Measures (Raven's, Culture Fair, & IPAT-G)	8	1,527	0.13	0.13	0.25	0.21	-0.02	0.52	0.07	0.43	0.27	0.23
Medium (Job Zone 3)	4	826	0.09	0.09	0.20	0.11	0.06	0.34	0.02	0.38	0.22	0.12

Table 12. Continued

Predictor/Test	(1)	(2)	(3)	(4)	(5)	(6)	(7) 80% CrI		(8) 95% CI		(9)	(10)
	k	N	r_{obs}	SD_r	ρ_{op}	$SD\rho_{op}$	LL	UL	LL	UL	ρ_{ts}	$SD\rho_{ts}$
Abstract/Inductive Reasoning, & Other Measures	15	1,746	0.15	0.19	0.28	0.29	-0.09	0.66	0.11	0.46	0.31	0.32
Low (Job Zones 1 & 2)	2	251	-0.01	0.23	-0.01	0.37	-0.49	0.46	-0.57	0.54	-0.02	0.40
Medium (Job Zone 3)	6	851	0.15	0.14	0.31	0.22	0.03	0.59	0.08	0.54	0.34	0.24
High (Job Zones 4 & 5)	2	132	0.31	0.13	0.64	0.10	0.52	0.77	0.27	1.02	0.71	0.11

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion and predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 13. Crystallized Ability (Gc) and Job Performance

Predictor/Test	(1)	(2)	(3)	(4)	(5)	(6)	(7) 80% CrI		(8) 95% CI		(9)	(10)
	k	N	r_{obs}	SD_r	ρ_{op}	$SD\rho_{op}$	LL	UL	LL	UL	ρ_{ts}	$SD\rho_{ts}$
Validity of Crystallized Ability by Level of Job Complexity												
Overall	199	18,619	0.23	0.13	0.49	0.15	0.31	0.68	0.46	0.53	0.54	0.16
Low (Job Zones 1 & 2)	108	9,307	0.22	0.12	0.45	0.11	0.30	0.60	0.40	0.50	0.50	0.13
Medium (Job Zone 3)	58	6,603	0.23	0.11	0.54	0.13	0.38	0.70	0.47	0.60	0.59	0.14
High (Job Zones 4 & 5)	27	2,214	0.29	0.15	0.59	0.17	0.38	0.81	0.48	0.71	0.65	0.18

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion <u>and</u> predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

Table 14. General Cognitive Ability (GCA) and Job Performance

Predictor/Test	(1)	(2)	(3)	(4)	(5)	(6)	(7) 80% CrI		(8) 95% CI		(9)	(10)
	k	N	r_{obs}	SD_r	ρ_{op}	$SD\rho_{op}$	LL	UL	LL	UL	ρ_{ts}	$SD\rho_{ts}$
Validity of General Cognitive Ability by Level of Job Complexity												
Overall	86	8,070	0.23	0.13	0.43	0.15	0.23	0.62	0.37	0.48	0.47	0.17
Low (Job Zones 1 & 2)	37	3,420	0.20	0.13	0.37	0.14	0.20	0.55	0.30	0.45	0.41	0.15
Medium (Job Zone 3)	31	2,456	0.25	0.15	0.48	0.18	0.25	0.71	0.38	0.58	0.53	0.20
High (Job Zones 4 & 5)	11	861	0.30	0.15	0.60	0.17	0.38	0.82	0.42	0.78	0.66	0.19
GCA and OCBs	7	871	0.09	0.11	0.18	0.11	0.04	0.32	0.03	0.33	0.20	0.12

Note: Column content is as follows: (1) k = number of independent samples (correlations); (2) N = total sample size; (3) r_{obs} = sample-size weighted mean observed correlation; (4) SD_r = standard deviation of the sample-size weighted mean observed correlation; (5) ρ_{op} = operational validity (sample-size weighted mean observed correlation corrected for indirect range restriction and criterion unreliability); (6) $SD\rho_{op}$ = standard deviation of the operational validity (ρ_{op}); (7) 80% CrI = 80% Credibility Interval around ρ_{op}; (8) 95% CI = Confidence Interval around ρ_{op}; (9) ρ_{ts} = true score correlation (sample-size weighted mean observed correlation corrected for indirect range restriction and unreliability in both the criterion <u>and</u> predictor); (10) $SD\rho_{ts}$ = standard deviation of the true score correlation (ρ_{ts}).

CHAPTER 6

DISCUSSION

Chapter Overview

I begin this chapter by briefly reviewing the key meta-analytic results from the previous chapter. I then discuss implications of the study findings for theory in light of recent research in the field of neuroscience. I conclude by discussing implications for practice, opportunities for future research, and study limitations.

Summary of Research Findings

The primary objective of the current study was to examine the relative validities of fluid and crystallized ability for predicting real-world performance. Drawing on findings from a diverse body of research on past performance, the nature of work, and expert performance, I argued that compared to measures of fluid ability, crystallized ability measures should more strongly predict real-world performance in the classroom as well as the workplace. My proposed hypotheses were meta-analytically examined using a large, diverse set of over 400 primary studies spanning the past 100 years. With regard to academic performance, measures of fluid ability were found to positively predict learning (as measured by grades). However, as hypothesized, crystallized ability measures were found to be superior predictors of academic performance compared to their fluid ability counterparts. This finding was true for both high school and college students.

Consistent with my hypotheses, similar patterns of results were observed with regard to both training and job performance. Again, crystallized ability measures were

found to be better predictors of performance than fluid measures. This finding was consistent at the overall level of analysis as well as for medium complexity jobs. The very small number of studies examining the relationship between fluid ability and performance for low and high complexity occupations severely limits the ability to make meaningful comparisons at these levels of analysis. However, this presents an interesting opportunity for future research. Likewise, for job and training performance, the relatively high validitites for fluid ability observed in a small number of high-complexity samples suggests that it is possible that compared to typical occupations, certain high complexity occupations are particularly reliant on fluid ability, thus making Gf equal to or greater than the validity of crystallized ability. For example, Goldberg (2009) has noted that some very complex computational tasks require both the left (the area responsible for pattern recognition) and the right (the area responsible for processing novel information) parts of the brain.

Hypotheses 4a and 4b were confirmatory in nature and addressed the previously observed gradient in test validity according to occupational complexity. Support was found for Hypothesis 4a, which argued that the validity of cognitive ability will increase as the level of job complexity increases. Although this idea was tested using an alternative method of assigning jobs to complexity categories, and using diverse measures of cognitive ability, the results remain consistent with Hunter's (Hunter, 1980; Hunter & Hunter, 1984) earlier findings which were based solely on GATB data. Likewise, support was found for Hypothesis 4b, which proposed that no such gradient will be visible for training performance. Consistent with this idea, the validities of Gc

and GCA measures for predicting training performance were found to be similar across low, medium, and high complexity occupations.

The question of whether the validities of cognitive ability tests differ under high vs. low stakes testing conditions is indeed an interesting one. The results in this regard were mixed. For crystallized tests, the results suggest that for high school students, low stakes testing situations produce somewhat higher observed validities than high stakes testing situations. However, this may be attributed to increased range restriction in high stakes testing situations. Sample size limitations prevented a more in-depth analysis of this issue in the current study. As hypothesized, Gc tests administered to college students displayed similar (or identical) validities under both high and low stakes conditions.

For GCA measures, the results were less than conclusive, and in some cases counter to hypothesis. The reason for this difference compared to the supporting findings for Gc measures is unclear; however there are several possible explanations. First, it is possible that the tests used to measure GCA under low stakes conditions varied qualitatively from those administered under high stakes conditions, and this in turn affected the validities. For example, under low stakes conditions, the Wonderlic Personnel Test was a frequently adopted assessment. On the other hand, under high stakes conditions traditional intelligence tests were more frequently employed. Likewise, it is possible that the coding scheme used to assign samples to low stakes and high stakes categories was less than satisfactory. Tests administered for both selection and assessment purposes were classified as high stakes. It is possible that a clearer difference would be seen had only selection tests been used. However, given that very few general cognitive ability tests were administered for selection purposes, this would have greatly

reduced the number of samples available for analysis. Finally, there is the possibility that

Hypotheses 3a and 3b are misspecified. Duckworth et al. (2011) acknowledged that test

motivation differences between high and low stakes testing situations had less effect for

predicting academic performance, compared with later life outcomes such as employment

or criminal convictions. Thus, the phenomenon may be more apparent when more distal

criteria are examined. Each of these possibilities will be examined in the future as an

expanded data set is compiled.

Regardless of the findings, utilizing validities which have been corrected using

accurate range restriction values should alleviate any major differences between high and

low stakes testing situations, should they truly exist. In their discussion of the issue,

Duckworth et al. (2011) do not acknowledge this as a possible solution to the potentially

inflated validities that may arise from low stakes testing. It is certainly worthy of

consideration.

<u>Implications for Theory</u>

Contemporary intelligence theory has placed great emphasis on the role of fluid

ability. For example, Vernon and Parry (1949, p. 234) have argued that Raven's

Progressive Matrices are "an almost pure g test" while Jensen (1998, p. 646) has

maintained that "factorially the PM apparently measures g and little else. . ." Following

this, researchers in management and psychology have adopted these tests as measures of

general cognitive ability (e.g., Edwards, Day, Arthur, & Bell, 2006; Schuelke et al.,

2009). Well-known intelligence batteries such as the Stanford-Binet have recently been

revised to include more explicit measures of fluid ability. Using structural and factor

analytic evidence, researchers such as Undheim (1981a, 1981b) and Gustaffson (1984)

have argued that Gf and *g* are essentially the same construct. However, the results of this study, which are based on criterion-related validty rather than factor-analytic evidence, demonstrate that Gc measures are superior predictors to Gf measures. This is contrary to what one would expect if Gf and *g* were indeed the same construct. Rather, the findings of this study are more consistent with General Cognitive Ability theory, which predicts that Gc indicators will be the best predictors of future learning and performance (which depends on learning).

Furthermore, it useful to consider some additional reasoning as to why Gf measures are not as robust predictors of performance as might be expected. The field of neuroscience offers some valuable insights in this regard. As briefly mentioned in Chapter 3, Goldberg (2009) summarizes rather persuasive evidence that the structure of the brain is functionally segmented to deal with both novelty (analogous to Gf) and pattern recognition (analogous to Gc). Specifically, recent research has shown that right side of the brain, which has been traditionally considered to handle most visual-spatial tasks, appears to be responsible for processing novel information. In contrast, the left side of the brain, traditionally known for language processing, appears to be the center of pattern recognition. When an individual encounters a novel situation, an unfamiliar face or symbol for example, both the left and right sides of the brain are activated simultaneously (Martin, Wiggs, & Weisberg, 1997). However, almost immediately, a process which Goldberg refers to as "cognitive gravity" begins to occur. This is a shift in responsibility from the right side of the brain to the left side of the brain. As the once novel face or symbol becomes familiar, the novel processing parts in the left side of the brain are no longer activated. When an individual encounters the once unfamiliar face in

the future, only the left (Gc) pattern processing part of the brain is activated. This

phenomenon has been demonstrated across a number of different types of tasks.

Furthermore, this shift can occur very rapidly, even while a single assessment instrument

is being administered (Goldberg, 2009).

Academic, training, and job performance do require the processing of novel

information. However, evidence from neuroscience suggests that once processed, novel

information quickly becomes crystallized. When this information is relied upon in the

future, it is recalled from the brain structures responsible for pattern recognition, not

those responsible for novelty. Therefore, it logically follows that efficiency in pattern

recognition is largely responsible for real-world performance. Cattell's Investment

Model proposed a similar "cognitive gravity" shift from Gf to Gc. However, in his

model the shift (from historical Gf to present Gc, Figure 6) was thought to take far longer

than is now known to be the case.

In the current study, the Gc measures adopted were broad measures which assess

the efficiency with which an individual has learned a variety of material over a long

period of time, in some cases 20 years or more. In contrast, fluid assessments measure

novel problem solving ability within a much shorter time frame, often under an hour.

This is a key difference in the scope of assessment, and may help explain the larger

validities for Gc measures. Even so, broad Gc measures are underestimates of the extent

to which an individual has learned over time. This is particularly the case for older

indiviudals. Both Cattell (1987) and Ackerman (2000) have noted that as individuals

grow older, they gain knowledge and expertise in increasingly narrower domains. In

turn, this poses a serious challenge for assessment as it is difficult to assess such

specialized knowledge across a diverse set of individuals. In contrast, broad Gc measures tend to assess the extent to which individuals have learned a common body of general material such as that learned during school. Gc includes a large number of *g* indicators, while Gf measures contain either fewer or only one indicator. This is another reason to expect Gc measures to have both higher construct validity and higher predictive validity.

The impact of Gf theory is also evident in newer models of ability assessment. Fagan and Holland (2009) have recently proposed an alternate method for assessing ability whereby students were "given information as to the meanings of previously unknown words, sayings, similarities, and analogies" (p. 62). Students' ability to learn these new words, sayings, similarities, and analogies was found to predict both class exam scores (uncorrected $r = .41$, corrected $r = .50$) as well as scores on a brief version of the SAT (uncorrected $r = .66$, corrected $r = .83$). These authors argue that this method offers a culture-fair method of predicting academic achievement. It is important to note that the content of the new knowledge items mirrored that of novel language items that are known to activate the left (novelty of Gf) side of the brain. Likewise, the entire training and testing session lasted only 40 minutes. This suggests Fagan and Holland's measure is likely assessing Gf or working memory.

The current study also raises questions about assumptions which are inherent in Cattell's Investment Model as well as PPIK. Both theories suggest that motivation plays a key role in the development of Gc. However, this may not be the case. For example, Roznowski (1987) administered gender-specific knowledge tests to male and female high school students.   Tests were constructed using 400 general knowledge items designed to have a male advantage (e.g., mechanics, farming, fishing, sports) or female advantage

(e.g., home economics, theatre and ballet, etiquette, clerical checking). Roznowski found that scores for both males and females were correlated with scores on a traditional Gc intelligence assessment. In fact, after making corrections for measurement error, scores on the interest tests correlated nearly perfectly with Gc. The fact that the knowledge tests measured a large number of interest domains, and the fact that male knowledge items were predictive for females and vice versa suggests that motivation was not a primary factor in acquiring the knowledge. Given this, future theoretical and empirical work should revisit the role of motivation in acquiring crystallized knowledge. It may very well be the case that capable individuals learn regardless of the specific interests or motivation.

<u>Implications for Practice</u>

Human resource decision makers are frequently tasked with the challenge of identifying selection tools which will help them optimize their workforces. Likewise, academic administrators at selective institutions are constantly seeking to identify the most capable students. Cognitive ability tests are one of the strongest predictors of academic performance (Kuncel et al. 2001, Kuncel et al., 2004), and the single best predictor of job performance (Schmidt & Hunter, 1998). As such, these tests are often utilized for student and personnel selection purposes. Practitioners have numerous choices when choosing cognitive ability tests, and they must consider multiple factors when selecting specific tests for use within their organizations. Although test validity is among the most important, other factors include price, delivery format, administration time, and legal defensibility. The findings of this study offer some important information with regard to the issue of the validity of fluid, crystallized, and general cognitive ability tests.

Crystallized tests are the dominant tests used for academic selection purposes (Hunt, 2000), although general cognitive ability tests are also often used for assessment purposes in primary and secondary school systems. Although fluid ability tests do predict academic performance, the current results indicate that these tests are less valid than tests of crystallized or general cognitive ability. Given this, there appears to be little reason to consider adopting fluid ability tests for academic selection purposes, particularly if they are to be the sole cognitive assessment to be utilized. However, this does not mean that Gf tests are not useful for research purposes in academic environments, indeed they are. As previously noted, more research on the criterion-related validity is needed at all levels.

Within the workplace, crystallized and general cognitive ability tests dominate the landscape. However, it is important to note that fluid ability tests are also being used for personnel selection purposes, and these tests are actively marketed to HR decision makers. However, considerably fewer validation studies have examined the relationship between Gf and performance. Rather than provide primary validity data, some test publishers point to meta-analytic results (e.g., Schmidt & Hunter, 1998) which demonstrate that general cognitive ability measures are the best predictors of job performance. Such assertions suggest that the extant validity data on general cognitive ability tests generalizes to nonverbal, fluid tests. However, the findings of the current study suggest that this may not be the case. Across the overall sample of jobs, fluid ability tests were found to demonstrate lower validities than either crystallized ability measures or measures of general cognitive ability such as the Wonderlic or Otis. Further, at the overall level, the 80% credibility intervals for the operational validity of Gf included zero, suggesting the validity of Gf is not generalizable across all jobs. It should be noted that fluid ability tests such as the Raven's *do* appear to be valid predictors of job performance for medium-complexity jobs, which represent the majority of jobs in the U.S. economy (Hunter & Hunter, 1984, Schmidt & Hunter, 1998). Since they are valid

predictors, Gf tests will have selection utility (Schmidt & Hunter, 1998). Nevertheless, in the sample of studies examined in this thesis, fluid tests were less valid predictors than their crystallized or general cognitive ability counterparts. HR decision makers should be aware of these differences, as well as the fact that the existing validity evidence for fluid tests is based on considerably fewer primary studies than is the case for Gc or GCA tests.

Even if they are aware of lower validities, some decision makers may be attracted to the claim that nonverbal ability tests reduce group differences. Test publishers need to provide compelling evidence that this indeed the case. In fact, research and theory suggest that fluid tests may still demonstrate group differences despite the fact that they are nonverbal assessments (Brown & Day, 2006; Higgins & Sivers, 1958; Irwing & Lynn, 2005; Lynn & Irwing, 2004; Raven, 1989; Rushton, Skuy, & Fridjohn; 2002; Tulkin & Newbrough, 1968).   For example, Lynn and Irwing (2004; see also Irwing & Lynn, 2005) have found that compared to females, males tend to obtain higher mean scores on Raven's Progressive Matrices tests. In a meta-analysis of 57 studies, they estimated that the male advantage was .33 d, a difference equivalent to 5 IQ points (Lynn & Irwing, 2004).   Likewise, other studies have observed that black individuals tend to score approximately one standard deviation lower than white individuals (e.g., Brown & Day, 2006; Higgins & Stivers, 1958; Rushton, et al., 2002).   Finally, researchers have observed that there is a positive relationship between socioeconomic status and scores on fluid tests (e.g., Raven, 1989; Tulkin & Newbrough, 1968). For example, in the British standardization sample, Raven (1989) found a correlation of .22 between SES and Standard Progressive Matrices scores. He maintains that this is equivalent to a within-age correlation of .30.

Test-takers from developed economies are likely to be exposed to a variety of modern media (television, video games, puzzles/mazes) that result in their receiving higher scores on fluid ability tests. Greenfield (1998) presents a compelling case for this line of reasoning in her discussion of the Flynn Effect. Individuals from non-developed or less-developed countries, or lower socioeconomic backgrounds, may tend to score lower on such assessments as they have had less experience with the type of information being assessed in fluid tests. This line of evidence suggests that contrary to Gf – Gc theory, Gf scores may be more dependent on learning and on individual differences in motivation and interests than are broad (generic) Gc measures. This is the opposite of what is postulated in Gf – Gc theory.

Although sex, race, and socioeconomic status are important categories to consider with regard to potential group differences, the results of the current study suggest that age may be an even more important concern. As discussed in Chapter 2, there is strong empirical evidence that fluid ability scores decline with age. Fluid ability peaks between ages 26 and 35, then begins a steady, continual decline. In contrast, crystallized ability remains relatively stable. Consider two individuals that have the same level of Gc, one aged 25 and one aged 50. In this situation, the older individual will very likely score lower on a fluid ability test. Thus, when used for selection purposes, Gf tests will *underpredict* the performance of older workers, because research has shown that Gc measures are predictively unbiased. This is an acute concern given that the population is rapidly aging and the number of older workers is increasing.

Finally, decision makers are often rightfully concerned with applicant reactions to selection procedures. Applicants tend to react more positively when they perceive that

selection procedures have content validity or "face validity" (Rynes & Connerley, 1993).

That is, applicants prefer selection tools to be job related. In this regard, Smither and

colleagues (Smither, Reilly, Millsap, Pearlman, & Stoffey, 1993) have found that both

recently hired managers and recruiting/employment managers tend to rate cognitive tests

with concrete items such as vocabulary, written English, and mathematical word

problems as more job-related than cognitive ability tests that consist of more abstract

item types. Given this, applicants may react more negatively to fluid ability tests.

Smither et al. have argued that applicant reactions to selection procedures may affect test

motivation, the willingness to accept a position if offered, and the propensity to engage in

litigation if they perceive a selection procedure is unfair.

Future Research

As noted earlier, there is a need for additional primary studies that measure fluid

ability and performance. Research examining the validity of Gf at specific levels of

occupational complexity is acutely needed. Likewise, given that fluid ability declines

throughout the lifespan while Gc remains relatively stable, it would be interesting to

investigate the extent to which Gf and Gc differentially predict performance for

employees of different age groups. This may become increasingly important given the

aging population.

Researchers may also benefit from examining the role of Gf throughout the

employee's tenure. It may be the case that fluid ability measures are more important

early in an employee's tenure, as they are faced with novel tasks. Gf may become less

important over time, as skills become crystallized and workers access information from

recognizable patterns that have become established in the brain over one's working

lifetime (c.f., Goldberg, 2005, 2009). However, as discussed earlier in this chapter, it appears that novel information becomes crystallized at a rapid rather than a slow pace. To the extent this is indeed the case, validity differences according to job tenure would not be visible. Furthermore, research has found that as a predictor of job performanmce, GCA remains stable (Schmidt, Hunter, Outerbridge, & Goff, 1988) or increases (McDaniel, 1985) throughout an individual's work tenure (see Hunter & Schmidt, 1996 for a review). Thus, any finding that the validity of Gf declines with tenure would lie counter to this established phenomenon.

Finally, although Gf and Gc are posited to be independent constructs, they are in fact correlated. Given this, it would be useful to meta-analytically examine the strength of this relationship. Although such an investigation was beyond the scope of the current study, accurate meta-analytic estimates of the correlation between Gf and Gc would be useful in testing models of intelligence that contain both constructs.

<u>Limitations</u>

This study has several limitations. First, as mentioned previously, there were considerably fewer primary studies included in the meta-analyses that utilized measures of fluid ability. Likewise, the psychometric and normative data for these measures was notably lacking when compared to studies that utilized GCA or Gc measures of ability. These factors limit the ability to make meaningful comparisons, particularly at lower levels of analysis for moderators such as job complexity. In addition, a lack of appropriate primary study and normative data prevented the construction of artifact distributions specifically for fluid ability. As a result, artifact corrections in the Gf analyses were made using distributions from the GCA samples. It is possible that the true

artifact values in the collection of Gf samples differed substantively from those in the respective GCA distributions, although there is no reason to suspect this was actually the case. Nevertheless, as this data set is expanded in the future, an attempt will be made to locate more primary studies that have examined the relationship between fluid ability and performance.

Second, the classification procedure used to categorize measures into fluid and crystallized ability was qualitative in nature. Although a sincere effort was made to classify measures in the clearest manner possible, it is possible that some measures could be classified differently. This is most likely an issue when coding decisions were made between crystallized and GCA measures. To address this, measures were evaluated by two coders. Likewise, only measures that were overall or omnibus measures of ability were classified as GCA. Nevertheless, it is likely that much of the content of GCA measures is indeed crystallized in nature, as Hunt (2000) has argued. However, classification contamination, to the extent that it does exist, should serve to make the results presented here conservative estimates rather than overestimations.

Finally, due to time and resource constraints, as well as the large size of primary studies that met the inclusion criteria, this study used a representative sample of primary Gc and GCA studies rather than the entire population of available studies. Studies were selected to be representative of the population of available studies. Likewise, the current study was large by meta-analytic standards, incorporating data from 419 unique primary studies. Nevertheless, it is possible that the studies analyzed are not representative of the larger population of studies. To address this, future research is planned using a larger number of Gc and GCA studies. Given the sheer volume of validity data for cognitive

measures, it is unlikely that a fully comprehensive synthesis including all extant data will be accomplished. In this situation it is necessary to weigh the benefit of knowledge gained from examining a large, but less than comprehensive data set against the significant resources required to locate, code, and analyze the full population of studies. As Hunter and Schmidt (2004, p. 493) have noted, the latter is often impossible due to availability bias. They argue that this criticism "applies equally well to the narrative review, the usual alternative to meta-analysis. That a narrative review is not quantitative in no way mitigates the effects of any bias in the sample of studies."

Conclusion

Nearly a century ago, Boring (1924, p.35) concluded that "Intelligence is what the tests test." Although intelligence is certainly a latent construct that is greater than any one test, there is some truth to his famous statement. Assumptions that fluid ability tests are the *sin quo non* or gold standard measure of intelligence may be incorrect. Rather, the criterion-related validity evidence presented in the current study suggests that it is crystallized and general cognitive ability measures that appear to be the better predictors of performance. As such, general cognitive ability theory suggests that compared to Gf measures, Gc and GCA measures are better indicators of the construct of intelligence.

Although this thesis has focused on individual differences in ability and performance, it is perhaps useful to close with Goldberg's (2009, p.80) reminder that similar phenomenon to the ones examined here are visible in the larger culture as a whole:

> It can be argued that the whole history of human civilization has
> been characterized by a relative shift from the right hemisphere to
> the left hemisphere owing to the accumulation of ready-made

cognitive "templates" of various kinds. These cognitive templates are stored externally through various cultural means, including language, and are internalized by individuals in the course of learning as cognitive "prefabricates" of sorts. Any attempt to translate Vygotskian cultural-historical psychology into neuroanatomical terms will inevitably lead to this conclusion.

APPENDIX

CLASSIFICATION OF COGNITIVE ABILITY MEASURES

Table A1. Measures of Fluid Ability (Gf)

Abbreviation	Test Name
APIL-CFT	Ability Processing of Information and Learning Battery – Concept Formation Test
AR	Abstract Reasoning (Study-specific scale)
BTIS-F	Berlin Test of Intelligence Structure – Fluid Factor
CAB-IR	Comprehensive Abilities Battery – Inductive Reasoning
CFIT	Culture Fair Intelligence Test
D-48	D-48 Test (Dominoes Test)
DAT-AR	Differential Aptitude Tests – Abstract Reasoning
ETS-IR	ETS Test Kit – Inductive Reasoning
Gf	Fluid Ability Composite
GRT2-AR	General Reasoning Tests – Abstract Reasoning
GT-70/23	Group Test 70/23
IPAT-G	Institute of Personality and Ability Testing – Nonverbal Test of G
IR	Inductive Reasoning (Study-specific scale)
PMA-R	Primary Mental Abilities Tests – Inductive Reasoning Scale
PPP	Penrose Pattern Perception
RAPM	Raven's Advanced Progressive Matrices
RSPM	Raven's Standard Progressive Matrices

Table A2. Measures of Crystallized Ability (Gc)

Abbreviation	Test Name
ACB-AR	Army Classification Battery – Arithmetic Reasoning
ACB-RV	Army Classification Battery – Reading & Vocabulary
ACT	ACT Test – Composite
ACT-E	ACT – English
AFQT	Armed Forces Qualifying Test
ASVAB-AR	Armed Forces Vocational Aptitude Battery – Arithmetic Reasoning
ASVAB-MK	Armed Forces Vocational Aptitude Battery – Mathematics Knowledge
ASVAB-PC	Armed Forces Vocational Aptitude Battery – Paragraph Comprehension
ASVAB-WK	Armed Forces Vocational Aptitude Battery – Word Knowledge
BSQT	Bell Systems Qualification Test
BST-RC	Basic Skills Test – Reading Comprehension
BST-LS	Basic Skills Test – Language Skills
BST-M	Basic Skills Test – Mathematical Skills
CAB-V	Comprehensive Abilities Battery – Verbal Ability
CAB-N	Comprehensive Abilities Battery – Numerical Ability
CIVIL-RV	Civil Service Exam – Reading & Vocabulary (Study Specific)
COOP-R	Cooperative Inter-American Tests of Reading
CTBS-R	Comprehensive Test of Basic Skills – Reading
DAT-LU	Differential Aptitude Tests – Language Usage
DAT-NA	Differential Aptitude Tests – Numerical Ability
DAT-SN	Differential Aptitude Tests - Sentences
DAT-SP	Differential Aptitude Tests – Spelling
DAT-VR	Differential Aptitude Tests – Verbal Reasoning
EAS-VR	Employee Aptitude Survey – Verbal Reasoning
EAT	Educational Achievement Test (Math and Physics Proficiency)

Table A2. Continued

Abbreviation	Test Name
FIT-GRAM	Flannigan Industrial Tests – Grammar
GATB-N	General Aptitude Test Battery – Numerical Scale
GATB-V	General Aptitude Test Battery – Verbal Scale
Gc	Crystallized Ability Composite
GKT	General Knowledge Test (Study-specific)
GRT2-NR	General Reasoning Tests – Numerical Reasoning
GRT2-VR	General Reasoning Tests – Verbal Reasoning
HVT	Hebrew Verbal Test
IHSC	Iowa High School Content Examination
LT-V	Lorge-Thorndike Intelligence Test – Verbal Battery
LOGIC/DR	Logic/Deductive Reasoning (Study-specific)
MATH	Mathematical Reasoning (Study-specific)
MH	Mill Hill Vocabulary Scales
NDRT	Nelson-Denny Reading Test – Total Score
NDRT-C	Nelson-Denny Reading Test - Comprehension
NDRT-V	Nelson-Denny Reading Test - Vocabulary
NUM	Numerical Reasoning (Study-specific)
PAF-N	Personnel Assessment Form – Numerical
PAF-V	Personnel Assessment Form – Verbal
PL/PQ	ACER Higher Tests PL-PQ (Verbal & Quantitative Reasoning)
PMA-VM	Primary Mental Abilities Tests – Verbal Meaning
PMA-VF	Primary Mental Abilities Tests – Word Fluency
POST	Police Officer Selection Test – Total Score
POST-RW	Police Officer Selection Test – Reading & Writing
PROSEL	Humanities, Science, & Social Science Knowledge (Study- specific)

Table A2. Continued

Abbreviation	Test Name
PSAT	Preliminary Scholastic Aptitude/Assessment Test - Total
PTI-V	Personnel Tests for Industry – Numerical
PTI-V	Personnel Tests for Industry – Verbal
READ	Reading Comprehension (Study-specific)
SAT	Scholastic Aptitude Test – Total
SAT-M	Scholastic Aptitude Test - Math
SAT-V	Scholastic Aptitude Test - Verbal
SET-N	Short Employment Tests – Numerical
SET-V	Short Employment Tests – Verbal
SFPS-GKT	State Farm Personnel Survey – General Knowledge Test
SRA-A	SRA – Arithmetic
SRA-N	SRA – Numerical Ability
SRA-V	SRA – Verbal Ability
STAN-AR	Stanford Arithmetic Test
TABE-R	Test of Adult Basic English – Reading Scale
TEST21	Test 21 – District of Columbia (Verbal Reasoning)
VERBAL	Verbal Reasoning (Study-specific)
VOCAB	Vocabulary (Study-specific)
WAIS-C	Wechsler Adult Intelligence Scale - Completion
WAIS-I	Wechsler Adult Intelligence Scale – Information
WAIS-S	Wechsler Adult Intelligence Scale - Similarities
WAIS-V	Wechsler Adult Intelligence Scale - Vocabulary
WRVT	Wide Range Vocabulary Test

Table A3. Measures of General Cognitive Ability (GCA)

Abbreviation	Test Name
ACE	American Council on Education Psychological Examination
ADAPT	Adaptability Test
ALPHA	Army Alpha Examination
ALPHA-R	Revised Alpha Examination
AFQT-g	Air Force Qualifying Test – g Factor
CFAT	Canadian Forces Aptitude Test
CTMM	California Test of Mental Maturity
D-70	D-70 Intelligence Test
GATB-g	General Aptitude Test Battery – g Factor
GCA	General Cognitive Ability Composite
H-N	Henmon-Nelson Test of Mental Maturity for College Students
IQ	IQ – Mixed scales
K-A	Kuhlmann-Anderson Intelligence Tests
L-T	Lorge-Thorndike Intelligence Test
MILLER	Miller Test for High School Pupils
MORAY	Moray House Test
O-L	Otis-Lennon Mental Abilities Test
OSU	Ohio State University Psychological Test
OTIS	Otis Mental Ability Test
OTIS-SA	Otis Self-administering Mental Ability Test
OTIS-Q	Otis Quick Scoring Mental Ability Test
PINT	Pintner General Ability Test
PSI	Performance Skills Index
S-B	Stanford-Binet Intelligence Test
SIT	Slosson Intelligence Test
TERM	Terman Intelligence Test

Table A3. Continued

Abbreviation	Test Name
T-M	Terman-McNemar Tests of Mental Ability
TCS	Test of Cognitive Skills
W-B	Wechsler-Bellevue Full-Scale
WAIS	Wechsler Adult Intelligence Scale – Full Scale
WISC	Wechsler Intelligence Scale for Children – Full Scale
WPT	Wonderlic Personnel Test

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