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Crystallized intelligence and openness to experience: Drawing on intellectual-investment theories to predict job performance longitudinally

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CRYSTALLIZED INTELLIGENCE AND OPENNESS TO EXPERIENCE: DRAWING ON INTELLECTUAL-INVESTMENT THEORIES TO PREDICT JOB PERFORMANCE LONGITUDINALLY

by

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ABSTRACT

Various approaches to conceptualizing and measuring intelligence have been utilized throughout history. Despite the plethora of intelligence theories, the field of industrial and organizational (I-O) psychology has been largely dominated by the psychometric tradition of intelligence and Spearman's general factor theory of intelligence (*g*). Moreover, other approaches to intelligence (e.g., the developmental perspective) have generally been ignored by I-O psychology. This is puzzling given the widespread acceptance among I-O psychologists of intelligence's substantial and increasing importance in the modern workplace.

Supported by a vast amount of research, *g* has often been recognized as the single best predictor of job performance. However, traditional measures of *g* have reached a plateau in terms of predictive validity for work-related criteria. Although *g* is not the sole determinate of job performance, failing to incorporate advancements from other fields (e.g., developmental psychology, cognitive psychology) is a potential limitation to continued improvement of job-performance prediction. One modern approach to intelligence that holds promise for improving our prediction of performance in the workplace is known collectively as the intellectual-investment theories, which posit that intellectual development is partially influenced by investment traits (e.g., Openness to Experience) that guide how, where, and when individuals invest their cognitive ability.

Stemming from this investment, individual differences in crystallized intelligence (Gc), a particular type of intelligence that largely increases throughout one's lifespan, are thought to result.

Using the intellectual-investment framework, this study sought to improve the prediction of job performance longitudinally by accounting for both intelligence and personality. To this end, latent-growth modeling was applied to archival personality, crystallized-intelligence, and job-performance data obtained from 92 employees. Overall, no support was found for the intellectual-investment framework in predicting job performance longitudinally, but a theoretical contribution was made and the study offers practical suggestions based on theory and research. In addition, a number of limitations to this study are discussed that are believed to contribute to the lack of support. In conclusion, the intellectual-investment framework offers the potential for improved job performance prediction and as such, this study offers suggestions that researchers can incorporate into future studies.

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DEDICATION

This dissertation is affectionately dedicated to my mother, Rebecca Anne Grochau. It was my mother who always encouraged me to reach for the stars. My hope is that my outstretched hands someday approach her reach towards the heavens.

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CHAPTER ONE

INTRODUCTION

Due to the increasing complexities and constant change of the modern workplace, intelligence has arguably become one of the most important individual-difference predictors of job performance (Gatewood, Feild, & Barrick, 2007). Indeed, research in industrial and organizational (I-O) psychology has pointed to intelligence's importance in personnel selection (Schmidt & Hunter, 1998). In particular, research suggests that intelligence is the single best predictor of success on the job (Hunter & Hunter, 1984; Schmidt & Hunter, 1998). Although debate about the use of intelligence testing in the workplace continues (e.g., social and legal ramifications), there appears to be widespread acceptance of intelligence's importance in the field of I-O psychology (Murphy, Cronin, & Tam, 2003). Moreover, Murphy et al. (2003) found that among the I-O psychologists who responded to their survey about the use of cognitive ability in the workplace, the vast majority believed that intelligence would continue to increase in importance as the requirements for successful job performance rise in complexity.

Despite its perceived importance in I-O psychology, Scherbaum, Goldstein, Yusko, Ryan, and Hanges (2012) argued that little research has been conducted on the underlying nature and measurement of intelligence over the last few decades. In other fields (e.g., developmental and cognitive psychology), advancements have been made in the understanding of intelligence (Reeve, Scherbaum, & Goldstein, 2015; Scherbaum &

Goldstein, 2015). Moreover, modern intelligence research has provided new insights about the construct, yet the field of I-O psychology has been slow to use and integrate these developments (Reeve et al., 2015; Scherbaum et al., 2012). Incorporating these advances (e.g., modern intghelligence theory) from other fields could provide I-O psychology with positive benefits, including the improvement of job-performance prediction (Agnello, Ryan, & Yusko, 2015; Reeve et al., 2015).

Why is it the case that I-O psychology has not adopted these new findings? As some have argued (e.g., Goldstein, Zedeck, & Goldstein, 2002; Murphy, 1996), I-O psychology's success at providing evidence of the generalizable relationship between intelligence and job performance has largely inhibited further investigation into the nature of intelligence. Indeed, Goldstein et al. (2002) suggested that there is a tendency in I-O psychology to view the relationship between intelligence and job performance as being an open-and-shut case. Given its importance, it seems time that I-O researchers and practitioners reopen the case of intelligence and incorporate advancements and findings from other fields to improve the understanding of human behavior at work (Agnello et al., 2015; Goldstein et al., 2002; Reeve et al., 2015; Scherbaum et al., 2012). The theories from which a researcher adopting this position has to choose are many and result from a complex, centuries-long process of development; accordingly, to narrow the pool of candidate theories for adoption, an exploration of the history of intelligence conceptualization and testing is necessary. To this end, the study will address this research gap by incorporating modern intelligence theory (intellectual investment theories) that postulates that certain personality traits (e.g., Openness to Experience) influence the development of a specific cognitive ability (i.e., crystallized intelligence).

Thus, accounting for both personality and intelligence is expected to better predict job performance longitudinally, which will benefit both researchers and practitioners in the I-O psychology field.

Historical Overview of Intelligence Testing

The notion of some individuals being more clever and gifted than other individuals has likely always existed in human culture and civilization (Chamorro-Premuzic & Furnham, 2005). Despite this length of time, a universally-accepted definition of the intelligence or cognitive-ability (an alternative label) construct, which describes individual differences in "mental capabilities" (Ones, Dilchert, & Viswesvaran, 2012), remains elusive (Neisser et al., 1996; Sternberg, & Detterman, 1986; Wechsler, 1975). In particular, different fields of study frequently create definitions of intelligence that place greater emphasis on certain aspects over others, often completely excluding particular aspects (Wechsler, 1975). In applied psychology, Ones et al. (2012) noted a particularly useful definition of intelligence, offered in Gottfredson (1997). They defined intelligence as,

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

Many other definitions of intelligence have existed (Wechsler, 1975) and one likely reason for such diversity is the importance associated with understanding and developing adequate measures for the construct (Scherbaum et al., 2012). Indeed, numerous such attempts have been made throughout history. From an historical perspective, Chamorro-Premuzic and Furnham (2005) argued that the scientific study of and attempt to conceptualize individual intelligence have their origins in the 1800s. Yet, others (e.g., Bowman, 1989; Doyle, 1974; Dubois, 1965, 1970) have argued that understanding the importance of and the capability to measure intelligence dates further back in human history.

Doyle (1974) indicated that around 2,500 years ago, the ancient Greeks used ability testing designed to encompass and assess the different aspects that characterized an ideal member of Greek society. Ability testing was used to supplement ancient Greece's educational system and aid in the personnel selection for state services (Anastasi, 1993; Doyle, 1974). As such, the Greeks were very interested in the theory and practice of both mental and physical testing (Doyle, 1974). Moreover, historical records, particularly in the writings of Aristotle and Plato, indicate the Greeks were interested in assessing individuals' future ability level given their current ability (aptitude testing) as well as their cumulated body of knowledge (achievement testing; Doyle, 1974). Although testing physical ability was often emphasized to a greater extent, mental achievement and aptitude tests were utilized, but to the ancient Greeks, the notion of such tests were largely informed by the characteristics of what they considered to be an ideal member of society (Anastasi, 1993; Doyle, 1974).

The Greek's conceptualization of intelligence was not exactly the same as other ancient societies. The ancient Chinese, for instance, widely used ability testing for a variety of purposes (Bowman, 1989; Dubois, 1965, 1970). In roughly 150 BCE, the emperors of the Qin or early Han dynasties implemented written examination programs (Bowman, 1989). While non-written selection assessments may have existed prior to this time, written examinations were used in selecting individuals for civil service positions. In addition, the written examinations were used to occasionally reevaluate the abilities of the selected officials. Dubois (1970) noted that an ancient Chinese emperor used examinations every three years to assess whether his officials were still capable of continued service. Despite their use in selection and evaluation, ability testing experienced a decline after the Qin or early Han dynasties, but reemerged in ancient China around the T'ang dynasty (618-906 CE; Bowman, 1989).

With the arrival of the Ming dynasty (1368-1644), Bowman (1989) noted that the civil service examinations had become highly developed and a formal social institution. The examinations were used to select individuals for positions among different levels (i.e., municipal, county, provincial, national). Moreover, examination results helped assign individuals formal titles and as Bowman (1989) described, "at each level, [examination] success yielded further titles and access to more power in the civil service" (p. 557). The system had become quite sophisticated by the height of the Ming dynasty, efficiently differentiating talent to serve positions at different levels of government. To the ancient Chinese, talented individuals were "those who showed very high levels of verbal cleverness and the capacity to build up elegant, abstract arguments with almost the quality of word games" (Bowman, 1989, p. 578). Hence, the Chinese assessed ability in a more linguistic sense, than did the ancient Greeks. Testing in the civil service system continued to develop for hundreds of years, which in essence made ability testing very much a part of Chinese society. Indeed, compared to the ancient Greek's "test-influenced society" (Doyle, 1974), Dubois (1965) argued that ancient China was a "test-dominated society." Yet, despite China's long history of testing, the modern view of intelligence is largely influenced by work done during the 1800s. That being said, the Chinese tradition is still meaningful to modern intelligence theory due to its large focus on linguistic skill, which is similar to crystallized ability, a more recent concept that will be discussed later.

Anastasi (1993) argued that the modern ability testing movement could be traced back to the work of Francis Galton. Moreover, Galton is often credited for influencing the foundation of a science devoted to studying mental abilities (Chamorro-Premuzic & Furnham, 2005; Reeve & Bonaccio, 2011). Influenced by his cousin Charles Darwin's (1859) theory of natural selection, Galton (1865, 1869) suggested that "genius" was largely hereditary and introduced the notion of general mental ability as an individual difference factor into the field of psychology (Reeve & Bonaccio, 2011). Further, Galton (1869), primarily through the study of giftedness within families, considered general mental ability (as opposed to specialized abilities) as the primary individual characteristic responsible for differences among individuals pursuing intellectual activities. The combination of such information influenced Galton (1869) to argue that the human population could be improved if two individuals with desirable traits produced offspring. As Galton (1865) explained, "if talented men were mated with talented women, of the same mental and physical characters as themselves, generation after generation, we might produce a highly-bred human race" (p. 319). Thus, Galton realized that a systematic way to measure such characteristics was needed (Anastasi, 1993); measures that "had been so developed as to embrace every important quality of mind and body" (Galton, 1865, p. 165).

In Galton's (1883) *Inquiries into Human Faculty and its Development*, he proposed that to measure one's intellectual strengths and weaknesses, a number of mental tests should be administered. Beginning in 1884, Galton started using various tests to collect data from the general public at his London-based Anthropometric Laboratory. The tests assessed different aspects of a person, including muscle strength, sensory discrimination, motor coordination, reaction time, and physical features (e.g., height, weight; Galton, 1888). These mental tests were the basis of his "theory of cognitive abilities" (Carroll, 1993, p. 31). This conceptualization of intelligence differed from the ideal-member-of-society and linguistic approach of the ancient Greeks and Chinese, respectively. That is, Galton believed different aspects of a person (e.g., height, muscle strength) collectively indicated one's intelligence. Moreover, Galton thought the differences observed on the tests could serve as a representation of an individual's mental ability capacity (Galton, 1883). Hence, Galton did not focus on the ideal characteristics of society members or linguistic ability. The idea that intelligence could be assessed using aspects of a person (e.g., muscular strength, weight) would be attempted by another researcher as well.

James Cattell adopted a similar measurement approach to studying intelligence as that of Galton (Anastasi, 1993). J. M. Cattell (1890) identified and used ten tests thought to measure fundamental psychological functioning of mental ability. The mental tests included measures such as tactile discrimination, memory, sound reaction time, and hearing (J. M. Cattell, 1890). However, the evaluations of J. M. Cattell's mental tests were discouraging. As Anastasi (1993) noted, the performance (or score) on one test had little relationship with the performance on another test. Moreover, performance across the tests had low correspondence to academic and life outcomes, which suggested the tests were not a proxy for intelligence. In short, the results were a disappointment. However, the lack of empirical support for the basic sensory functioning approach to intelligence (examined by Galton and J. M. Cattell) suggested a need for a new approach. Indeed, in the years that followed, another approach to conceptualizing and measuring intelligence would expand the understanding of intelligence.

Instead of measuring intelligence solely through basic sensory functioning, Alfred Binet proposed an alternative approach that attempted to capture complex, higher-order mental processes (Binet, 1903). Binet and Simon (1905/1916) believed intelligence consisted of an important capability and as the authors noted, "this faculty is judgment" (p. 42). They further explained, "to judge well, to comprehend well, to reason well, these are the essential activities of intelligence" (p. 43). In 1904, the government of France provided Binet the opportunity to identify learning-challenged schoolchildren, which afforded him the chance to translate his conceptualization of intelligence into practice (Anastasi, 1993). As a result of this, Binet and Simon (1905/1916) created a standardized measure of intelligence that attempted to capture both judging and reasoning ability.

The items used in Binet and Simon's (1905/1916) intelligence scales were chosen based on two primary purposes (Ackerman, 2013). The first was differentiation by age, which assumed, on average, that intelligence abilities increased with age. As such, older children were expected to outperform younger children on a more difficult item (all things being equal), item difficulty being determined by the proportion of children (across all chronological ages) successfully completing an item. Moreover, young children with high intelligence tend to become older children with high intelligence (the same being true for lower intelligence). Items that failed to meet this assumption were not included in the assessment. The reader may note that items failing to meet this assumption could have been insensitive to age-related differences or inversely sensitive or that the removed items may have been tapping some other capability. Thus, excluding such items may have limited further refinements to their conceptualization of intelligence. Secondly, multiple items that comprised an intelligence scale were expected to be associated with school outcomes (i.e., success, failure). That is, intelligence scales were kept in the assessment if they correlated with school outcomes. The reader may note that the removed scales could have been tapping another outcome (e.g., ability to solve novel problems outside of the school domain). The scores obtained on the scales were indicated by "mental age," which was based on average chronological age performance. Namely, an individual with a mental age of 9 performed as well as the average 9-year-old. Binet and Simon's intelligence scales had an incredible impact on the measurement of intelligence. Indeed, Mackintosh (2011) described its importance as having "formed the basis of modern [intelligence] tests" (p. 14).

While a few researchers examined the application of Binet-and-Simon-type ability scales to the study of adults, the first large-scale assessment of adult intelligence was created during the First World War (Ackerman, 2013). During World War I, the U.S. Army wanted a test that could assess adult intelligence and be administered to large numbers of individuals. Because the Binet-and-Simon-type intelligence tests required one-on-one administration by a qualified psychological assessor, they were too costly and inefficient for assessing large number of U.S. Army recruits (Mackintosh, 2011). As such, the president of the American Psychological Association, Robert Yerkes, guided the development efforts to create mass-administered intelligence tests. Two tests resulted from these efforts; namely, the *Army Alpha* for literate individuals and *Army Beta* for illiterate individuals (Ackerman, 2013). The Army tests measured intelligence in a way that "mirrored the Binet scales in content (e.g., tests of arithmetic, analogies, general information, synonyms and antonyms)" (Ackerman, 2013, p. 120). Thus, the ideas of measuring intelligence did not change drastically from Binet and Simon, but the test format certainly did. With the new test format, over a million individuals were assessed during the war effort (Ackerman, 1996). Mackintosh (2011) noted the impact saying, "the Army tests…wrought a transformation in the public's attitude to mental tests" (p. 17). Indeed, following World War I, commercially available intelligence tests have been widely used in both educational and organizational settings (Wasserman & Tulsky, 2005). Though various conceptualizations and measurement practices have been embraced throughout history, this adoption of Binet's approach to intelligence had theoretical implications for this new era of testing. Namely, the focus on complex higher-order mental processes largely ignored other intellectual capabilities that developed over time, such as the ancient Chinese's assessment of language ability. However, the considerations of intellectual abilities that develop over time (e.g., vocabulary) have recently reemerged in modern theories of intelligence (e.g., R. B. Cattell, 1943). That being said, the advancement of mass-administered intelligence tests that measure complex mental processes made during World War I effectively ushered in a new age of intelligence testing that has continued to influence our thinking about intelligence.

Psychometric Tradition of Intelligence

Since the advent of statistical techniques in the early 1900s, there have traditionally been two approaches to studying intelligence; namely, the psychometric and the developmental perspective (Reeve & Bonaccio, 2011). The distinction between the two approaches corresponds roughly to either focusing on the underlying structure of basic cognitive ability (i.e., psychometric perspective) or the acquisition of knowledge and skills (i.e., developmental perspective). The former has primarily used quantitative methods (e.g., factor analysis) when investigating intelligence, while the latter has often focused on understanding how knowledge acquisition occurs over time. Though theories of intelligence have been developed that better integrate the two perspectives (e.g., Ackerman, 1996; R. B. Cattell, 1943), the field of I-O psychology has largely remained dominated by the psychometric perspective of intelligence (Agnello et al., 2015; Reeve et al., 2015; Murphy et al., 2003; Scherbaum et al., 2012; Schmidt & Hunter, 1998).

The origins of the psychometric approach to intelligence largely resulted from the work of Charles Spearman (1863-1945; Agnello et al., 2015). In 1904, occurring around the same time as the work of Binet and Simon, Spearman was influenced by Galton's proposals of intelligence. Indeed, Spearman (1904) examined the relationship between sensory discrimination (e.g., weight, light, visual) and intelligence in school children. Spearman (1904) found individual differences in sensory discrimination to be strongly related to what he deemed "General Intelligence," but much of his later research would focus on his observation of commonalities among different ability tests and their relationship with children's school grades (Drasgow, 2003). Spearman (1904) described the highly intercorrelated tests and grades saying, "whenever branches of intellectual activity are at all dissimilar, then their correlations with one another appear wholly due to their being all variously saturated with some common fundamental function" (p. 273). That is, mental activities appearing unrelated (e.g., math, language, music) generally show similar patterns (e.g., individuals good in math tend to be equally good in language) and as such, the similarities are due to an underlying, single factor. Hence, a single factor could generally account for the high interconnectedness among the tests and grades, though each variable (e.g., tests, grades) had varying levels of saturation with the single factor. He described a variable's saturation with the single factor as the "extent to which the considered faculty is functionally identical with General Intelligence" (p. 276).

Spearman's (1904) findings implied that individuals that performed well on one intelligence test would likely perform well on another intelligence test. Indeed, he referred to this phenomenon of only positive intercorrelations as "positive manifold" (Reeve & Bonaccio, 2011). That is, similar performance on different intelligence tests (e.g., math, verbal) would be observed if the tests were positively related. However, he understood that a single underlying factor could not explain all the variance associated with each variable (e.g., course grades) and the remaining variance could be explained by statistical error, unique variance, or both, which led him to propose a two-factor theory of intelligence (Carroll, 1993; Spearman, 1927). The superordinate factor was signified as *g* (or general mental ability) and the subordinate factor consisted of many specific abilities, not one particular ability. As such, Spearman presumed that *g* influenced performance in every domain and that specific abilities accounted for the variance *g* did not explain in specific domains (e.g., math course grade, music; Drasgow, 2003). That is, performance in a domain was influenced by a combination of *g*, a domain specific factor, and statistical error.

Through his study of *g*, Spearman introduced a new statistical methodology (i.e., factor analysis) that could be implemented in the study of intelligence. Spearman (1904) provided a way to determine the amount of saturation a variable had with *g*. In essence, the saturations described by Spearman were factor loadings derived from simple formulae (Carroll, 1993; Drasgow, 2003). The importance of factor analysis' introduction in the study of intelligence cannot be overstated. Indeed, Reeve and Bonaccio (2011) recognized its importance saying, "the use of factor analysis in the study of cognitive abilities is in many ways equivalent to the use of the telescope in the study of astrological bodies" (p. 192). Yet, the use of factor analysis in research is not without controversy and debate (Osborne & Fitzpatrick, 2012). For instance, debate remains over the best extraction techniques, when certain rotation techniques are appropriate, the decision rule regarding the number of factors one should extract and interpret, how large a sample size one needs, and the generalizability of the results (e.g., Costello & Osborne, 2005; Henson & Roberts, 2006; MacCallum, Widaman, Preacher, & Hong, 2001). Hence, factor analysis is more of an art than a precise science. Moreover, unlike factor analysis, the telescope in astronomy is likely not surrounded by such controversy and debate; thus, the comparison is imperfect.

Louis Thurstone made further methodological contributions through his study of intelligence. Similar to Spearman, Thurstone (1938) believed that intelligence consisted of an organized structure that could be shown through statistical analysis of ability tests. That is, he assumed the patterns among different ability tests would provide evidence of a systematic structure of intelligence. However, unlike Spearman, Thurstone proposed a multifactor model of intelligence that explicitly rejected a unitary notion of intelligence (i.e., *g*). To investigate his model, he administered 56 tests to 218 University of Chicago students. Thurstone (1947) developed multiple factor analysis to analyze the data and found, after extracting and rotating, seven mental abilities (i.e., perceptual, memory, inductive reasoning, numerical, verbal relations, spatial, word fluency) that he believed contributed to intelligence (Thurstone, 1938). However, Spearman (1927, 1939) critiqued Thurstone's model noting that the factor analysis technique used did not allow for *g* to be inferred, if indeed it existed. As such, Spearman re-analyzed Thurstone's data using a statistical technique that allowed, but did not require, the extraction of *g* (Spearman, 1939). The re-analysis results showed that *g*, in addition Thurstone's seven mental abilities, could be obtained. Later, Thurstone (1947) acknowledged that the seven mental abilities were correlated and the extraction of *g* was conceivable.

Despite the differences between Thurstone and Spearman, their models of intelligence were not fundamentally different (Carroll, 1993). Both allowed for *g* and more specific factors to exist. In essence, the difference was primarily whether one placed greater emphasis on *g* or the more specific factors. Other psychometric representations of intelligence were later developed. For example, Vernon (1950) developed a hierarchical model in which *g* influenced the lower levels of intelligence. Two primary factors (i.e., verbal-education and spatial-mechanical) were positioned at the next level below *g*. Each of the two primary factors were minor factors consisting of specific skills. Though Vernon (1961) considered *g* to largely account for individual differences within a domain, differences in specific skills would also likely contribute. In contrast to a hierarchical model, Guilford (1967) proposed the Structure of Intellect (SOI) model, which suggested that the abilities contained in the model were independent of one another or uncorrelated. Hence, the model excluded *g*. However, the SOI model has been criticized for being illogical in nature and inconsistent with empirical findings (Carroll, 1993; Reeve & Bonaccio, 2011).

The psychometric models of intelligence presented do not represent an exhaustive list, but the models help illustrate the similarities, despite some differences on the surface. As Carroll (1993) noted, "all of them assume an organization of abilities whereby some abilities are more general than others" and the different number of abilities recognized by the models depended to some degree on "the factorial methods available to, or favored by, the authors of these models" (p. 62). Moreover, the psychometric representation of abilities is important to understanding the structure of intelligence, but as Kelley (1939) stated, "evidence of existence of a factor…[should not be] cited as evidence that it is important" (p. 141). Despite Kelley's comment, much of the psychometric study of intelligence has "focused on the statistical properties of standardized performance test, producing a lack of theoretical knowledge on the nature of the processes underlying individual differences in intelligence" (Chamorro-Premuzic & Furnham, 2005, p. 29).

Current State of I-O Intelligence Research

Meta-analytic evidence and arguments presented in Schmidt and Hunter (1998, 2004) appear to have persuaded the field of I-O psychology of g's importance in staffing organizations (Reeve et al., 2015; Schneider & Newman, 2015). Indeed, g is often credited as being the best single predictor of performance on the job, generally producing a medium effect size (Cohen, 1992). As such, measuring specific cognitive abilities for personnel selection has been considered not worth the time (Hunter, 1986; Ree, Earles, & Teachout, 1994) and specific cognitive abilities (e.g., quantitative reasoning; visual-spatial ability) have often only produced a small (according to Cohen, 1992) amount of additional predictive power over g (Reeve et al., 2015). Spearman's (1927) "indifference of the indicator" principle seemed to provide further justification for I-O psychology's focus on measuring g (Ree & Carretta, 2002). Jensen (1992) summarized Spearman's principle saying, "all cognitive tests are vehicles of g…and it has proved impossible to devise a mental ability test that is not g loaded to some degree" (p. 275). Thus, regardless of the measure of intelligence used (e.g., a specific cognitive ability measure), the results obtained reflect, to some extent, a measurement of g (not entirely the intended specific cognitive ability).

Whether due to the aforementioned measurement issues or one or more other factors, the field of I-O psychology has essentially embraced a unitary view of intelligence that stems from a psychometric view of deriving the structure of intelligence, mathematically, from the shared commonality among a battery of intelligence tests; an embracement that has hindered conversation and debate about other approaches to intelligence (Scherbaum et al., 2012). That being said, the embracement of a psychometric approach was not unjustified or without research support. In terms of usefulness, *g* has been incredibly successful at predicting job performance and other human behaviors in the workplace (Murphy, 1996). The success led some (e.g., Ree & Earles, 1991) to claim that there is "not much more than *g*." As such, this has prompted many in I-O psychology to conclude that intelligence theories do not offer much more beyond the field's current knowledge and that specific cognitive abilities, compared to *g*, provide little value in the prediction of job performance (Reeve et al., 2015).

Despite *g*'s success in I-O psychology, measures of *g* have not continued to improve the prediction of job performance. In particular, Ackerman and Beier (2012) noted, "traditional measures of *g* have reached a plateau in terms of predictive validity for job-relevant criteria" (p. 150). That being said, it is important to note that *g* is not the only determinate of performance on the job (e.g., motivation, personality; Gatewood et al., 2007). However, with regard to using measures of *g*, one potential limitation to continued improvement of job performance prediction is a lack of theoretical consideration to lifespan cognitive development in *g* theories (van der Maas et al., 2006). I-O psychology has appeared to adopt Spearman's notion of intelligence being innate and fixed (Ackerman & Beier, 2012). Other intelligence theorists (e.g., R. B. Cattell, 1987) have argued for and incorporated developmental changes in intelligence, such as the idea that increases in overall knowledge can result from occupational and educational experiences. Indeed, longitudinal evidence suggests that adult intelligence scores remain fairly stable over the short term, but gains and losses in mental ability have been observed over the long term (Schaie, 1996). Yet, the use of a unitary-factor *g* model in I-O psychology is inadequate to explain both the pattern of growth and decline in ability observed in longitudinal studies (Finkel, Reynolds, McArdle, & Pedersen, 2007; McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002; McArdle, Hamagami, Meredith, & Bradway, 2000). That is, all intellectual abilities are considered a linear function of *g* and as *g* increases, the abilities should increase in proportion to their relationship with *g* (Nisbett et al., 2012). However, intellectual abilities differ in their developmental trajectories (e.g., some abilities begin to decline in early adulthood, others decline in old age), and as such, *g* "yields an overly simplistic view of growth and change over age" (McArdle et al., 2002, p. 115).

Unless I-O psychology takes into account ability development over time, the field is "likely to remain stuck in a rut" (Ackerman & Beier, 2012, p. 151) with regard to using intelligence to understand and predict behavior at work. Granted, a long-term view of intelligence may not appeal to organizations and researchers merely concerned with short-term outcomes (e.g., job performance) due to employees frequently changing jobs; however, it stands to reason that numerous employees remain with a sole organization for longer periods of time (e.g., several years; Ackerman & Beier, 2012). Despite some employees experiencing long job tenure, I-O psychology has largely failed at incorporating research findings and exploring theoretical notions from different intelligence approaches that would attempt to provide answers to such developmental issues (e.g., reasoning ability decline) likely to affect employees over time (Ackerman & Beier, 2012; Reeve et al., 2015; Schaie, 1996; Scherbaum et al., 2012). Consequently, I-O psychology has lagged further behind in the pioneering research and knowledge on intelligence (Scherbaum et al., 2012).

However, I-O psychology's embracement of other intelligence approaches could improve real-world objectives (e.g., enhanced job performance prediction, develop intelligence measures with lower adverse impact) and galvanize the field's stagnated research agenda for intelligence (Agnello et al., 2015; Reeve et al., 2015). One such approach, known collectively as the intellectual investment theories (Ackerman, 1996; R. B. Cattell, 1943; von Stumm & Ackerman, 2013), holds promise for I-O psychology intelligence research (e.g., accounting for change in ability over time, incorporating personality traits thought to influence cognitive development); a review of its origins and development is beneficial to understand its application to the workplace.

Historical Origins of Intellectual Investment

Raymond Cattell proposed a model that divided intelligence into two basic forms; namely, fluid and crystallized intelligence (R. B. Cattell, 1943), commonly denoted as Gf and Gc, respectively (Drasgow, 2003). The model stemmed from a developmental view of intelligence and "has evolved into one of the most influential psychometric models of intelligence" (Reeve & Bonaccio, 2011, p. 195). The development of his Gf-Gc model was the result of a number of influences (R. B. Cattell, 1971, 1987). Among these influences, R. B. Cattell (1971, 1987), a student of Charles Spearman, noted that the perceptual or cultural-free intelligence tests (spatial, non-verbal) used in Spearman's laboratory clustered together (particularly when applied to children) and were distinct from the education-oriented intelligence tests, which suggested that such tests comprised a different facet of *g*. Likewise, perceptual tests and education-oriented *g* tests showed different age-related changes (e.g., steady performance declines on perceptual tests began at earlier ages than did declines on education-oriented tests). In addition, the evidence from Thurstone's (1938) multifactor model seemed to indicate more than a single factor of intelligence. Another influence stemmed from R. B. Cattell's experience creating culture independent intelligence measures, which according to Carroll (1984), "undoubtedly" contributed to the creation of his fluid and crystallized theory of intelligence.

Carroll (1984) noted that through the span of approximately 20 years (1930s-1950s), R. B. Cattell devoted much attention to intelligence testing and development. In particular, R. B. Cattell placed importance on the creation of measures that assessed intelligence in a manner that was not culturally dependent. That is, test content representative of universal knowledge, not culturally based knowledge. Indeed, R. B. Cattell contended that many of the available intelligence tests were largely based on culturally acquired knowledge (Cattell & Bristol, 1933). Moreover, R. B. Cattell believed it was possible to design an intelligence measure for individuals originating from diverse cultures, the content of which contained largely universal knowledge (R. B. Cattell, 1940). To R. B. Cattell (1940), these cultural-free, common knowledge test items could assess intellectual reasoning and as a consequence culture group comparisons could be made.

In 1940, R. B. Cattell designed a test that contained visual content he believed was not culturally dependent. The visual items, based on other developed intelligence tests (e.g., The Spearman Visual Perception Test), included mazes, image series, classification (i.e., identifying the unrelated item(s) among a group of items), sequence and relation matrices, and mirror images. Although the words fluid and crystallized were not in the culture-free test papers (Carroll, 1984; R. B. Cattell, 1940; Cattell, Feingold, & Sarason, 1941), the spatial, non-verbal items used in the culture-free intelligence test closely resemble the content contained in what R. B. Cattell and others (e.g., R. B. Cattell, 1971, 1987; Horn & Cattell, 1967) later deemed Gf measures (e.g., Raven's Progressive Matrices). Likewise, the culture-free test displayed age-related relationships similar to those later observed on tests of fluid ability (e.g., stronger performance earlier in development; R. B. Cattell, 1971, 1987; Horn & Cattell, 1967). Indeed, Cattell and colleagues (1941) compared the culture-free test with other popular intelligence tests during the time such as The Terman-Merrill revision of the Binet and the Arthur Performance Test. The results of the study showed that children performed better on the culture-free test than did highly cultured adults, a finding that is consistent with age-related differences in Gf. Thus, R. B. Cattell's work on the culture-free intelligence test along with other influences (e.g., findings from Spearman's laboratory) impacted the development of his Gf-Gc theory (Carroll, 1984; R. B. Cattell, 1971, 1987).

In R. B. Cattell's (1943) "*The Measurement of Adult Intelligence*," he proposed several ideas that would form the basis of his Gf-Gc model of intelligence. According to R. B. Cattell (1943), Gf "has the character of a purely general ability to discriminate and perceive relations between any fundaments, new or old…[and] increases until adolescence and then slowly declines" (p. 178). In contrast, Gc "consists of discriminatory habits established in a particular field, originally through the operation of fluid ability, but not longer requiring insightful perceptions for their successful operation" (p. 178). In addition, he detailed the psychometric properties of intelligence tests noting such tests measure a combination of both Gf and Gc at every age, but Gf largely determines test performance in childhood, whereas Gc determines more of the test performance in adulthood.

R. B. Cattell's (1943) model of intelligence was posited "almost simultaneously" with Hebb's (1941, 1942) ideas of human intelligence (Ackerman, 2013). A neuropsychologist, Hebb (1939) studied individuals with brain injuries using intelligence tests to assess overall general intellectual functioning as well as verbal and non-verbal skills. He examined a series of intelligence test results from individuals with damaged or removed brain tissue. Hebb (1941, 1942) noticed that brain injuries affected individuals differently at various stages of human development. In particular, individuals with brain injuries sustained in early development (infancy) tended to display lower overall general intelligence scores and verbal ability in later stages of development. In contrast, individuals with brain trauma occurring in middle or late development (adulthood) showed minimal to zero decline in overall general intelligence or verbal ability. These findings suggested to him that adult intelligence consisted of two distinct aspects; namely, Intelligence A and Intelligence B (Hebb, 1942). According to Hebb (1942), intellectual development involved "(A) the development of direct intellectual power…and (B) the establishment of routine modes of response to common problems" (p. 289).

R. B. Cattell (1943) noted the similarities between his Gf-Gc theory and Hebb's Intelligence-A and Intelligence-B ideas saying, "Hebb has independently stated very clearly what constitutes two thirds of the present theory" (p. 179). In addition, several others scholars (e.g., Ackerman, 1996; Carroll, 1984) have also noted the similarities. For example, R. B. Cattell conceived of Gf as relating to abstract reasoning, learning novel material, and general engagement of higher-order mental operations and processes (e.g., inductive reasoning; Ackerman, 2013; Drasgow, 2003). Likewise, Hebb's Intelligence A involved similar processes as Gf (e.g., abstract reasoning, solving new problems; Ackerman, 2013). Moreover, both Gf and Intelligence A were thought to peak early in individual development and decline with increasing age (R. B. Cattell, 1943; Hebb, 1942). Gc, on the other hand, was considered to be representative of an individual's diverse range of knowledge and skills (e.g., language, general information) acquired through experience and education (Ackerman, 2013; R. B. Cattell, 1943; Drasgow, 2003). Similarly, Intelligence B encompassed the same aspects as Gc (e.g., knowledge and skills an individual acquires over time; Ackerman, 2013; Hebb, 1942). Furthermore, Gc and Intelligence B were believed to be well maintained over one's lifespan (Ackerman, 2013). Although the Hebb and R. B. Cattell's theories of intelligence were similar, Hebb did not continue to develop his theory much in the ensuing years, while R. B. Cattell continued to refine and expand his Gf-Gc theory in the subsequent years (Ackerman, 2013).

Gf-Gc Theory and G

In his first empirical study of Gf-Gc theory, R. B. Cattell (1963) administered several ability measures from the Culture Fair Intelligence Test (e.g., matrices, classification) and Thurstone Primary Mental Abilities Tests (e.g., verbal, spatial, reasoning) to 7th and 8th grade students. R. B. Cattell observed some ability measures such as verbal and reasoning were highly related to one factor (Gc), while scores on other measures such as matrices, spatial, and classification were highly related to a different factor (Gf). Thus, he found support for "the existence of two general ability factors" (p. 20). In addition, John Horn, a student of Raymond Cattell, empirically tested Gf-Gc theory and introduced refinements to the theory with Cattell (e.g., Horn, 1965, 1968; Horn & Cattell, 1966, 1967). Indeed, Horn (1965) and Horn and Cattell (1967) found age-related changes support for Gf-Gc theory. That is, the authors observed a decline in Gf and an increase in Gc with age. The reader may note that age-related changes Horn and Cattell (1967) observed question the differentiation-by-age assumption of Binet and

Simon. Through empirical investigations, Horn (1965) found additional factors to Gf and Gc (e.g., Gv or visualization) and later, other identified ability factors and refinements were added to Gf-Gc theory (e.g., Horn, 1968; Horn & Cattell, 1967). In essence, the Horn-Cattell model was a hierarchical model that did not concede a higher-order g-factor as the only explanation for the positive manifold between second-order (e.g., Gf, Gc, Gv) factors (Carroll, 1993; Horn, 1968; Reeve & Bonaccio, 2011). That is, positive manifold permits the influence of only g, but equally allows for many influences only loosely associated (Horn, 1968).

Horn and Cattell (1966) noted that Gf-Gc theory "seriously questions the notion that there is a unitary structure which can be designated general intelligence" (p. 253). Likewise, Schneider and Newman (2015) argued that intelligence is not unidimensional due to a large amount of empirical evidence suggesting multidimensional and hierarchical models accounting for different factors of intelligence (e.g., Gf, Gc, verbal ability, spatial ability) provide better fit than do unidimensional models (though unidimensional models of intelligence do not result in horrible fit). Providing support for this notion, Carroll (1993) conducted one of the most comprehensive examinations of the psychometric structure of intelligence. He reanalyzed 461 data sets from previous factor-analytic studies of intelligence. From his reanalysis, a three-stratum structure of intelligence was identified (Figure 1), with a general mental ability factor (*g*) in the third stratum that accounted for the most variance. Moreover, in the second stratum, Gf and Gc were most strongly related to *g*. The first stratum contains narrow abilities that represent each second stratum factor. The results were highly consistence with Gf-Gc theory and as such, McGrew (1997, 2005, 2009) proposed a conceptual unification known as the

Carroll-Horn-Cattell (CHC) model of intelligence. Despite the common framework (CHC), differences between the theories remained.

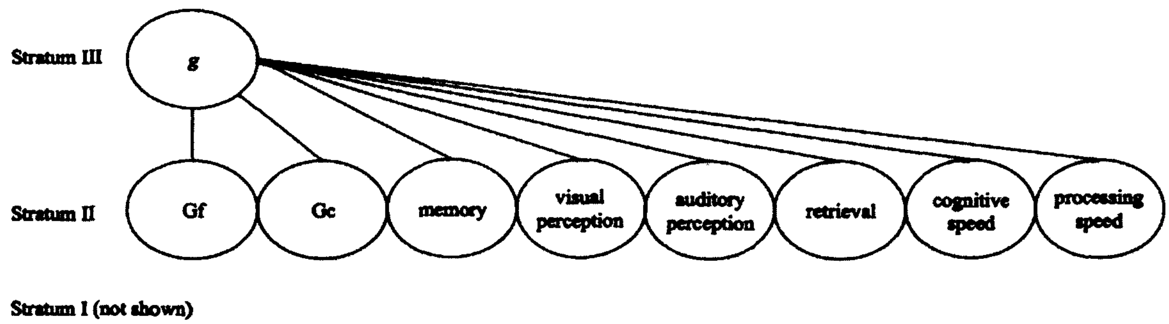

Figure 1 *Carroll's Three-stratum Model of Intelligence.*

Adapted from *Handbook of Psychology*: Industrial and Organizational Psychology (p. 115), by F. Drasgow, 2003, Hoboken, NJ: Wiley & Sons. Copyright 2003 by John Wiley & Sons, Inc.

Schneider and Newman (2015) argued that the main difference between the two theories is *g* being at the top of Carroll's (1993) hierarchical theory, whereas Horn favored (e.g., Horn & Blankson, 2005) a hierarchical model that included the broad correlated factors in the second stratum, explicitly objecting to a *g*-factor. R. B. Cattell (1963) did not entirely object to a *g*-factor, but his interpretation slightly differed from others (e.g., Spearman). R. B. Cattell (1963) summarized his initial empirical study of Gf and Gc stating, "these two general abilities appear in a single third-order factor hypothesized to express the "formative fluid ability" partly responsible for the present level of both of them" (p. 20). That is, previous fluid ability or "historical fluid intelligence" in stratum three (as opposed to *g*) caused the Gf and Gc in present day (Figure 2; R. B. Cattell, 1971, 1987). Indeed, Carroll's (1993) results found both Gf and Gc to be most strongly related to his *g*-factor, which supports R. B. Cattell's (1963) notion of what the general factor represented and caused. As such, empirical evidence supports Gf-Gc theory as a psychometric representation of intelligence as well as its lifespan cognitive developmental hypotheses (e.g., Gf declines in early development, Gc increases with age). Hence, Gf-Gc theory better integrates the psychometric and developmental perspectives of intelligence than sole *g*-theories (Reeve & Bonaccio, 2011).

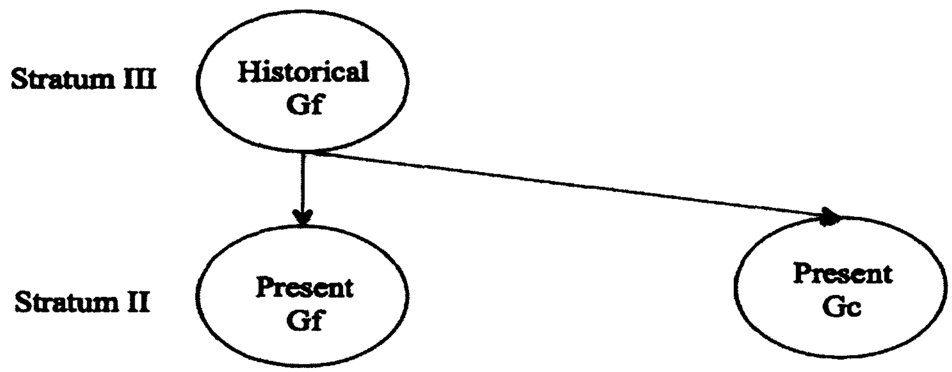

Figure 2 *Cattell's Investment Theory*

Adapted from *Intelligence*: Its Structure, Growth, and Action (p. 146), by R. B. Cattell, 1987, New York, NY: Elsevier Science. Copyright 2003 by Elsevier Science Publishers.

Development of Intellectual Investment Theories

Despite Gf-Gc theory better integrating the psychometric and developmental perspectives of intelligence, the developmental aspects have not been extensively investigated. Indeed, numerous empirical investigations have been conducted on the psychometric structure of Gf-Gc theory, but less recognized and researched is the developmental aspect of Gf-Gc theory known as Investment Theory (Figure 2; Ackerman, 1996; R. B. Cattell, 1971, 1987; Thorsen, Gustafsson, & Cliffordson, 2014). The basic ideas of R. B. Cattell's (1971, 1987) Investment Theory were evident in the early development of Gf-Gc theory, though he did not explicitly reference Investment

Theory in these early works (e.g., R. B. Cattell, 1943). When describing Gc, R. B. Cattell (1943) stated it "consists of discriminatory habits long established in a particular field, originally through the operation of fluid ability" (p. 178). That is, the investment of fluid ability over time causes, to a large degree, the development of Gc (R. B. Cattell, 1963, 1971, 1987). Moreover, a reciprocal causal relationship between Gf and Gc is not maintained in the theory (Schmidt & Crano, 1974). In other words, one's current level of Gf is thought to be independent or unaffected by one's previous accumulated Gc. In addition, other factors like personality and motivation were thought to affect (to a lesser degree) the investment of Gf into Gc. Indeed, R. B. Cattell (1963) speculated that further investigation into Gf-Gc theory may uncover "a number of personality and dynamic factors (e.g., super ego [sic] strength, emotional stability) affecting the investment of fluid intelligence in crystallized intelligence skills" (p. 10).

The most extensive discussion of Investment Theory was first presented in R. B. Cattell's (1971) *Abilities: Their structure, growth, and action* and later in R. B. Cattell's (1987) *Intelligence: Its structure, growth, and action.* An extension of the psychometric structure of Gf-Gc theory, Investment Theory proposed a causal relationship between Gf and Gc and as such, implies that individual differences observed in Gc are contingent on levels of Gf. To R. B. Cattell (1987), Gf is considered "a single, general, relation-perceiving ability....applicable to any sensory or motor area" (p. 138). The term "fluid" is used since it is not restrained to any sensory or motor area or tied to particular habits (R. B. Cattell, 1987). The rate at which one learns tasks, especially complex tasks (e.g., reading, mathematics, abstract reasoning), is largely dependent on Gf levels (though other factors such as quality of teaching and individual motivation will affect learning).

Stemming from the learning process (e.g., experience, practice), these acquired abilities such as knowledge and "high-level judgment skills" result in Gc "because their expression is tied to a series of particular areas" (R. B. Cattell, 1987, p. 139). That is, unlike Gf, Gc is constrained to particular habits or certain areas (e.g., sensory, motor). Though R. B. Cattell (1987) believed the investment of Gf largely accounted for acquired Gc, he acknowledged that "years at school, interest in school work, and other influences [would] also determine, perhaps substantially, the level of crystallized abilities" (p. 139).

As previously discussed, R. B. Cattell interpreted the third-order *g*-factor (high correlations among broad abilities or positive manifold) as representing historical Gf (R. B. Cattell, 1971, 1987). Hence, a positive relationship between one's performances on two distinct Gc assessments (e.g., vocabulary, general knowledge) is largely accounted by historical Gf. Moreover, one's present-day Gc level "is a function of last year's fluid ability level - and last year's interest in school work and abstract problems generally" (R. B. Cattell, 1987, p. 139). Thus, one hypothesis that stems from Investment Theory is the idea that present-day Gc level is a partly due to previous levels of both Gf and Gc (Thorsen et al., 2014). Another hypothesis that follows is previous Gc levels should not affect one's current Gf levels. These propositions of Investment Theory have been examined empirically (e.g., Ferrer & McArdle, 2004; Gustafsson & Undheim, 1992; McArdle et al., 2000; Rindermann, Flores-Mendoza, & Mansur-Alves, 2010; Schmidt & Crano, 1974; Thorsen et al., 2014), but the results have varied; some found support, while other findings were inconclusive. In short, R. B. Cattell's Investment Theory remains more of a theoretical explanation of cognitive development than a robust, empirically-supported phenomenon.

Motivational-Experiential Theory of Intelligence

Similar to R. B. Cattell's cognitive development ideas, Hayes (1962) proposed a motivational-experiential theory to help explain intellectual differences that occur among individuals over time. According to Hayes (1962, p. 303), the theory involved four main points:

> (a) Differences in motivation may be genetically determined. (b) These motivational differences, along with differences in environment, cause differences in experience. (c) Differences in experience lead to differences in ability. (d) The differences commonly referred to as intellectual are nothing more than differences in acquired abilities.

The theory implies that differences in motivation affect cognitive development in so much as it drives an individual to pursue learning activities and intellectual-stimulating environments. Hence, initial motivational levels, to a large degree, account for life-span differences in cognitive ability.

Hayes' definition of intelligence closely resembled that of Gc. As he described, "manifest intelligence is nothing more than an accumulation of learned facts and skills" (Hayes, 1962, p. 337). The accumulation of knowledge and abilities in Hayes' (1962) theory suggests that the investment of motivation (as opposed to Gf) contributes to observed differences in intelligence. Like R. B. Cattell's ideas on the heritability of Gf, Hayes believed variations in initial motivation levels were largely innate; but he rejected the notion of an inborn general factor of intelligence. Thus, the primary difference between the two theoretical approaches was on the existence of an inherited cognitive-ability capacity and its impact on intellectual development.

R. B. Cattell (1971, 1987) acknowledged that motivation and interest in school played a part in his Investment Theory, but Gf (an innate intellectual capacity) was primarily responsible for the trajectory and capability of one's overall cognitive development. In contrast, Hayes (1962) argued against a predetermined intellectual capacity influence. Instead, he assumed that motivation levels directed individuals towards (and away from) particular learning activities, which in turn, lead to different intellectual capabilities over time. That is, all individuals are born with the ability to achieve any level of cognitive ability (through learning experiences), but innate motivation levels to pursue intellectually-engaging opportunities largely accounts for observed differences in ability. Building on the ideas of both R. B. Cattell and Hayes, Ackerman (1996) proposed an investment theory of cognitive development that considers the collected influence of different human aspects (e.g., personality, interests) in the development of intelligence.

Intelligence-as-Process, Personality, Interests, and Intelligence-as-Knowledge Theory

Ackerman (1996) proposed an integrated intellectual investment theory known as intelligence-as-process, personality, interests, and intelligence-as knowledge (PPIK). Based largely, but not exclusively (e.g., Hayes, 1962; Hebb, 1942), on R. B. Cattell's (1971, 1987) Investment Theory, PPIK suggests a causal relationship from intelligence-as-process to intelligence-as-knowledge. Intelligence-as-process reflects fluid-type abilities (physiological-based), whereas intelligence-as-knowledge reflects crystallized-type abilities (experience- and educational-based; Ackerman, 2000). Like R. B. Cattell, Ackerman (1996) believed individual differences in intelligence-as-knowledge were partly due to ability (intelligence-as-process), but personality traits and interests were also believed to determine the differences to the extent to which they influenced intellectual investment of said ability. Moreover, Ackerman (1996) posited that abilities and interests develop together, such that ability level determines the likelihood of success on a particular task, and the motivation to engage in a task stems from both interests and personality. Successful performance on tasks increases interest in the task domain and subsequently, an individual's task- and domain-specific knowledge increases. Unsuccessful task performance, however, decreases interests and likely hinders any future development of domain-specific knowledge.

Intelligence-as-knowledge and Gc are similar in nature (Ackerman, 1996). Intelligence-as-knowledge is believed to form the basis of adult intelligence and contain the domain-specific knowledge of adult intellect (Ackerman, 2000). According to Ackerman (2000), domain-specific knowledge includes acquired information about occupations, academic studies (e.g., medicine, law), hobbies, functioning of a government, etc. As such, domain-specific knowledge in the PPIK model develops in a similar manner as Gc in that both accumulate over time. However, commonly used assessments of Gc typically do not measure the broad construct of adult intellect (Ackerman, 1996, 2000). Gc tests are generally designed to measure acquired experience knowledge (Carroll, 1993). For instance, these tests usually measure consensus or culturally-acquired knowledge such as language abilities (e.g., vocabulary, understanding synonyms, spelling), not domain-specific knowledge (e.g., job- or occupation-specific knowledge; Ackerman, 1996; Carroll, 1993). Given the numerous aspects of intelligence-as-knowledge, Ackerman (2000) acknowledged the difficulties in adequately measuring its full breadth and depth. That being said, von Stumm and Ackerman (2013) noted that

Gc assessments are considered markers or proxies of intelligence-as-knowledge, and by extension adult intellect, because such measures typically assess intelligence built and developed over time. As mentioned before, this development of adult intellect is thought to be guided, in part, by personality traits; so-called intellectual investment traits (Ackerman & Heggestad, 1997; Ackerman & Rolfhus, 1999; Goff & Ackerman, 1992). As such, understanding the associations between personality and intellect is useful in better understanding the intellectual-investment-theories framework and in particular, the reason investment traits have been hypothesized to contribute to the development of cognitive ability.

Investment Trait: Openness to Experience

Intellectual investment traits are defined as "stable individual differences in the tendency to seek out, engage in, enjoy, and continuously pursue opportunities for effortful cognitive activity" (von Stumm, Chamorro-Premuzic, & Ackerman, 2011, p. 225). Investment traits, on the one hand, are believed to help explain individual differences in the pursuit of learning activities, such as going to galleries and museums, solving puzzles and riddles, and reading newspapers (Soubelet & Salthouse, 2010; von Stumm & Ackerman, 2013). On the other hand, investment traits may help individuals construct experiences (e.g., exotic, mundane) in an intellectual stimulating way that promotes cognitive growth and development (Kashdan, Rose, & Fincham, 2004; Stine-Morrow, 2007). Ackerman's (1996) intellectual investment traits and Hayes's (1962) motivational drives refer to the same tendency; namely, an overall learning orientation (i.e., hunger for knowledge; von Stumm & Ackerman, 2013). However, Hayes believed that learning orientation was the sole source for individual differences in cognitive ability, whereas Ackerman allowed for reciprocal effects between intelligence-as-process, intellectual investment traits, and interests, to account for differences in intelligence-as-knowledge. While all investment theories agree that intelligence is a continuing process that develops into adult intellect, the mechanisms (e.g., intellectual investment traits) underlying the development are not fully known. That is, it is also possible that higher intelligence levels enable individuals to pursue learning opportunities (i.e., ability precedes the development of intellectual investment traits) or that greater acquired knowledge produces hunger for additional knowledge (i.e., prompting learning engagement), but von Stumm and Ackeramn (2013) argued that adult cognitive development is most plausibly due to a mutual development and shared reciprocal influence between intellectual investment traits and intelligence.

An abundance of investment traits have been identified (see von Stumm & Ackerman, 2013 for a review), but the most frequently used proxy for investment traits is Openness to Experience, a personality trait within the Five Factor Model (Costa & McCrae, 1992) and a vital part of Ackerman's (1996) PPIK model. The trait Openness to Experience describes individuals being intellectual curious, imaginative, pursuing variety, exploring their emotions and inner feelings, holding unconventional values, and having aesthetic appreciation (Costa & McCrae, 1992). Individuals with these particular characteristics arguably spend more time learning new information and attempting to solve novel problems (Ziegler, Danay, Heene, Asendorpf, & Bühner, 2012). Moreover, individuals high on Openness to Experience prefer and are more likely to encounter new, intellectually-stimulating situations, which involves encountering new information and enjoying numerous learning experiences (von Stumm et al., 2011; Ziegler et al., 2012).

As such, these activities plausibly lead to further development and strengthening of knowledge and Gc (Chamorro-Premuzic & Furnham, 2005; von Stumm et al., 2011).

A positive relationship between Openness to Experience and general intelligence has been shown consistently (e.g., Judge, Jackson, Shaw, Scott, & Rich, 2007; Woo, Chernyshenko, Stark, & Conz, 2014). However, Ackerman and Heggestad (1997) found that Openness to Experience was more strongly related to Gc than Gf. Likewise, von Stumm (2013) found that Openness to Experience had a stronger association with intelligence-as-knowledge than with intelligence-as-process, and after adjusting for intelligence-as-process, Openness to Experience's relationship with intelligence-as-knowledge reduced, but remained significant. Moreover, von Stumm and Ackerman (2013) found that five of the six facets of Openness to Experience (the exception being Actions) were positively related to Gc. Providing longitudinal support for the theory, Ziegler et al. (2012) found that Openness to Experience positively affected cognitive-development changes. Moreover, the authors found support for the interplay between Openness to Experience and Gf on the development of Gc, thus providing support for Openness to Experience as an intellectual investment trait and the investment theories of cognitive development.

Adult Development of Gc

Although a number of longitudinal studies have demonstrated that individual differences in cognitive ability remains fairly stable over time (e.g., Conley, 1984; Deary, 2000, 2001; Deary, Whalley, Lemon, Crawford, & Starr, 2000), a pattern of within-person variability generally emerges. That is, cognitive ability is much more stable over the short term, than over the long term. To provide some clarification for this phenomenon, let us return to the empirical evidence on age-related changes in Gf and Gc. In 1966, Horn and Cattell argued that the mixed results (e.g., some finding intelligence increased, decreased, and/or remained fairly constant with age) observed in previous studies on age-related changes in intelligence could be explained by the degree to which the researchers measured various levels of Gf and Gc. To this end, Horn and Cattell (1966, 1967) demonstrated that Gf negatively correlated with age, while Gc positively correlated with age. The initial findings from Horn and Cattell have largely been consistent with subsequent empirical studies on age-related changes in intelligence (see Schaie, 1996 for a review).

Gc, in contrast to Gf, has been found to increase throughout much of one's lifespan (e.g., Horn & Cattell, 1967; Kaufman, Johnson, & Liu, 2008; Schaie, 1996). Indeed, Gc has been estimated to continue to increase until around the age of 70, an age that most working adults are retired by in the United States, and then slowly decreases afterwards (e.g., Schaie, 1996). Moreover, adult peak performance on crystallized-type ability tests has been shown to occur later in age (e.g., late 30s), and then present a plateau or a gradual decline pattern (Ackerman, 2013). Likewise, middle-aged adults have been found to be more knowledgeable in many domain-specific areas compared to younger adults (Ackerman, 2000). Given the cumulative evidence demonstrating minimal decline over time, Gc has been referred to as a maintained ability (e.g., Horn & Blankson, 2005). Thus, on average, adults should display higher levels of Gc compared to their younger counterparts (Ackerman, 2013). That being said, what are the implications of accumulated Gc in an organizational context? Moreover, what role does Openness to Experience, an investment trait, play? Do they both contribute to job performance? To this end, exploring the Gc- and Openness to Experience-job performance relationships will help illuminate the applicability of the intellectual investment framework within an organizational setting.

Intellectual Investment Theories and Job Performance

Theoretical linkages between individual-difference predictors (e.g., intelligence, personality) and outcomes (e.g., job performance) play an important role in understanding work behaviors (Ones et al., 2012). Before detailing the conceptual and theoretical links of the Gc- and Openness to Experience-job performance relationship, job performance must be described. Job performance has been defined as observable behaviors individuals engage in that contribute both directly and indirectly to the goals of the organization (Campbell, McCloy, Oppler, & Sager, 1993). Moreover, job performance is generally considered multidimensional in nature (e.g., Campbell, McHenry, & Wise, 1990; Ghiselli, 1956), although the commonalities among performance measures suggest a higher-order, general factor of job performance (Viswesvaran & Ones, 2000; Viswesvaran, Schmidt, & Ones, 2005). As such, the following discussion will focus on overall job performance.

Gc and Job Performance

Conceptually, intelligence tests are related to job performance because, to a large extent, they assess an individual's ability for learning (Ones et al., 2012). This idea of one's learning ability is often contained in various definitions of intelligence. Indeed, the definition of Gc reflects the effectiveness to which an individual has previously learned (Postlethwaite, 2011). Empirically, strong links have been made between one's ability to learn and acquire knowledge and skills (as measured by intelligence tests), and the demonstration of actual learned skills and acquired knowledge across a variety of domains (e.g., academic, occupational; Kuncel, Hezlett, & Ones, 2004; Ones et al., 2012). Not surprisingly, Gc has been shown to be related to job performance (Postlethwaite, 2011). In fact, Postlethwaite (2011) found that crystallized ability was more strongly related to job performance than fluid ability. Several reasons help explain why crystallized ability is a robust predictor of job performance; namely, past performance, human aging, and the nature of work.

As previously discussed, Gc reflects previously learned knowledge. As such, measures of Gc capture an individual's past performance with respects to learning (Postlethwaite, 2011). This is in line with one of the most well established phenomena in Psychology. That is, one of the best predictors of future performance is past performance (e.g., Locke, Frederick, Lee, & Bobko, 1984; Oullette & Wood, 1998). For instance, undergraduate GPA was found to be related to desirable graduate school outcomes (e.g., overall GPA, performance on comprehensive exams; Kuncel, Hezlett, & Ones, 2001). Moreover, Gc measures assess both ability and other factors (e.g., motivation, time) of past performance. In the intellectual investment framework, Gc represents not only the knowledge an individual was able to learn, but also his or her investment (e.g., engagement in and pursuit of learning opportunities) across time (Ackerman, 1996; R. B. Cattell, 1971, 1987).

Occupational performance, to a large degree, is dependent on one's ability to master and understand the essential core of job knowledge (Postlethwaite, 2011). After mastering, the nature of work typically becomes more routine and less novel (Horn & Blankson, 2005). However, in some occupations (e.g., air traffic control, some creative fields, theoretical physics; Kanfer & Ackerman, 2004; Postlethwaite, 2011) individuals experience novelty to a larger extent, but such occupations are considered the exception rather than the rule. Thus, it has been hypothesized that intelligence is indirectly related to job performance. That is, intelligence is related to the acquisition of job knowledge, and in turn, job knowledge is related to job performance (Schmidt, 2002; Schmidt & Hunter, 1992; Schmidt, Hunter, & Outerbridge, 1986). Furthermore, the importance of job knowledge can be seen when viewed negatively. Indeed, with respects to low levels of job knowledge, Schmidt and Hunter (2004) stated, "not knowing what one should be doing— or even not knowing all that one should about what one should be doing—is detrimental to job performance" (p. 170). In terms of human development, Gc is largely accumulated and maintained over one's lifespan, whereas Gf begins to decline in early adulthood (Ackerman, 2013). Thus, if Gf were more critical for job performance (through knowledge acquisition), one would likely observe job performance mostly decreasing over time. However, Ng and Feldman (2008) found a small positive relationship between age and job performance, which supports Gc as being more central to job performance. Therefore, it follows that overall job performance is a partial proxy for job-specific knowledge.

Openness to Experience and Job Performance

Openness to Experience is conceptually related to job performance because the personality trait affects intrinsic motivation to learn (Major, Turner, & Fletcher, 2006; Minbashian, Earl, & Bright, 2013; Watanabe, Tareq, & Kanazawa, 2011), which is related to job performance. That is, individuals high on Openness to Experience typically have higher levels of learning motivation, which is related to job performance through its association with greater job knowledge and skill acquisition (Minbashian et al., 2013). Moreover, individuals high on Openness to Experience, in contrast to low, are not necessarily more capable of learning, but they are more prone to exhibit a mindset and perform behaviors that promote the acquisition of knowledge and skills (Rolfhus & Ackerman, 1999). Likewise, Openness to Experience is positively associated with the adoption of a learning goal orientation (Payne, Youngcourt, & Beaubien, 2007). Individuals with a learning goal orientation tend to use more effective learning strategies, set challenging goals, display greater effort and planning, and seek more feedback. Despite the conceptual links, empirical evidence has typically shown a weak relationship between Openness to Experience and job performance (Barrick, Mount, & Judge, 2001; Woo et al., 2014). One reason for the weak relationship may be due to the short time-interval (e.g., one year) commonly used in examining the personality and job performance relationship, which does not always account for the honeymoon effect (Minbashian et al., 2013).

The *honeymoon effect* (Helmreich, Sawin, & Carsrud, 1986) describes the idea of minimum performance differences among employees in the early stages of a job because motivation to learn and perform will be exhibited by new employees due to external influences. For instance, employees beginning a job will be aware that their performance is being monitored and evaluated; thus they will likely be motivated to perform initially, regardless of personality differences. Hence, short-term performance differences may not exist between employees with varying levels of Openness to Experience (all things being equal), but over the long term, higher levels of Openness to Experience will likely be more strongly related to overall job performance than lower levels. Openness to

Experience's stronger relationship over time is due to its association with intrinsic motivation to learn and learning goal orientation (Minbashian et al., 2013). Indeed, high Openness to Experience employees tend to continuously engage in learning activities throughout their careers, and as such, knowledge and skill acquisition continues to develop. Moreover, through learning goal orientation, these employees tend to seek mastery of tasks that will benefit their long-term performance, even at the expense of short-term performance (Harris, Mowen, & Brown, 2005). Empirically, evidence has shown support for Openness to Experience being a stronger predictor of job performance over time and being associated with slower performance deceleration and decline (Minbashian et al., 2013; Tett, Jackson, & Rothstein, 1991). Therefore, it follows that Openness to Experience, like intelligence, indirectly contributes to job performance by facilitating the acquisition of job-specific knowledge over time.

Time and Job Performance

The theme of time has been present throughout much of this paper, but the passage of time "is not particularly interesting to industrial and organizational (I/O) psychologists" (Beier & Ackerman, 2012, p. 721). Instead, the interesting aspects lie in the things that happen during the passage of time. For instance, people age, abilities change (e.g., decline, increase), employees develop skills, and individuals get promoted to new job positions. Indeed, it is well known that employee performance varies as a function of time (Dalal, Bhave, & Fiset, 2014). Ghiselli (1956) first noted the concept of dynamic criteria, which referred to "changes in the rank-ordering of individuals in their performance over time" (Barrett, Caldwell, & Alexander, 1985, p. 51). Likewise, Humphreys (1960) observed that past performance is not perfectly correlated with future performance. Different conceptual arguments have been offered to account for the observed temporal changes in employee job performance (see Beier & Ackerman, 2012; Lievens, Ones, & Dilchert, 2009); however, research has mostly ignored within-person performance changes due to normal human development (e.g., increased crystallized ability with age).

In the intellectual investment framework, the distinction between the different types of intelligences (i.e., Gf, Gc) and the incorporation of intellectual investment traits is important for a number of reasons; chief among them is accounting for both intelligence and personality. In particular, extensive research has examined the degree to which cognitive ability tests retain their predictive power over time (Barrett, Phillips, & Alexander, 1981; Campbell & Knapp, 2001; Deadrick & Madigan, 1990; Schmidt, Hunter, Outerbridge, & Goff, 1988), but only a few studies have examined the same for non-ability factors such as personality (e.g., Lievens et al., 2009; Minbashian et al., 2013). More scarce, however, is the examination of the combined influence of intelligence and personality on the prediction of job performance over time. Thus, the primary aim of this dissertation is to use modern intelligence theory (intellectual investment theories) that account for a specific type of intellectual ability (i.e., Gc) and personality traits theorized to facilitate cognitive development (i.e., Openness to Experience) to improve job performance prediction longitudinally.

Primary Hypotheses

Intellectual investment theories propose that personality traits determine how, where, and when individuals invest their cognitive ability (Ackerman, 1996; R. B. Cattell, 1971, 1987). Hence, differences in crystallized abilities or knowledge are believed to stem from general intelligence and the levels of investment. Empirical evidence supports the intellectual investment framework as an important theory for understanding and predicting employee job performance. Indeed, crystallized abilities have generally been shown to increase throughout adulthood (Horn & Cattell, 1967; Kaufman et al., 2008). Moreover, crystallized ability was recently shown to be a stronger predictor of overall job performance than fluid ability (Postlethwaite, 2011). In addition, as a proxy investment trait, Openness to Experience has been shown to contribute to the development of Gc over time (Ziegler et al., 2012). Meta-analytic evidence has generally not found Openness to Experience to be a strong predictor of job performance (Barrick et al. 2001; Woo et al., 2014), but the relationship is often examined in shorter time intervals (e.g., one year). However, longitudinal research and conceptual arguments suggest the relationship becomes stronger as a function of time (Helmreich et al., 1986; Minbashian et al., 2013). Thus, the following hypotheses were justified on the basis of the intellectual investment theories and research findings.

Hypothesis 1: Crystallized intelligence (Gc) will positively predict overall job performance over time.

Hypothesis 2: Employee age will positively predict crystallized intelligence (Gc).

Hypothesis 3: Openness to Experience will be positively related to crystallized intelligence (Gc).

Hypothesis 4: Openness to Experience will be a stronger predictor of overall job performance as job tenure increases.

Hypothesis 5: Compared to the independent prediction of each, the combination of crystallized intelligence (Gc) and Openness to Experience will more strongly predict overall job performance over time.

Research Question

A common perception exists that considers personality traits, which represent fairly stable patterns of feelings, thoughts, and behaviors, as relatively static (Roberts, Walton, & Viechtbauer, 2006). Yet, an individual's personality is subject to change (Specht, Egloff, & Schmukle, 2011). That is, several longitudinal studies have shown mean-level changes in personality traits across time (e.g., Haan, Millsap, & Hartka, 1986; Helson & Moane, 1987; Helson & Wink, 1992; Roberts, Caspi, & Moffitt, 2001; Robins, Fraley, Roberts, & Trzesniewski, 2001). However, personality theories differ in their prediction of how personality develops over a lifespan (Srivastava, John, Gosling, & Potter, 2003). Indeed, two prominent personality perspectives (i.e., biological and contextualist) hypothesize different age-related changes in personality.

The biological view of personality suggests a "plaster" hypothesis (Srivastava et al., 2003). In essence, the plaster hypothesis proposes that personality traits stop developing and changing by early adulthood, around the age of 30. The Five Factor Model of personality stems largely from a biological view. Indeed, McCrae and Costa (1996) postulated that personality traits result almost exclusively from biological origins and by early adulthood, they are fully matured (cf. Costa & McCrae, 2006). As such, minimal to no change is predicted after early adulthood. In contrast, the contextualist view of personality predicts plasticity (Srivastava et al., 2003). That is, personality traits are proposed to be multiply determined, and that they are subject to ongoing change throughout adulthood. Moreover, the change is thought to be due to many factors, and one's social environment is thought to be an important factor influencing the change (Haan et al., 1986; Helson, Jones, & Kwan, 2002). Empirical investigations have started to shed some light on these different hypotheses.

Using personality traits from the Five Factor Model, several research studies have examined the degree to which personality changes and whether age-related change patterns emerge (e.g., Roberts & DelVecchio, 2000; Roberts et al., 2006; Specht et al., 2011). The following discussion of these and other empirical findings will focus on the personality trait Openness to Experience, due to its important role in the intellectual investment theories. Examining the stability and consistent of personality, Roberts and DelVecchio (2000) found that people's Openness to Experience levels became less consistent the longer the time interval used to re-measure people's trait levels. Moreover, the authors observed that the stability of Openness to Experience generally increased with age (e.g., less stable in childhood, more stable in late adulthood). However, Openness to Experience never fully stabilized, which provides evidence against the plaster hypothesis suggesting personality traits stop changing in early adulthood. Despite the increased stability pattern observed, other empirical studies have found a more complex pattern.

Specht and colleagues (2011) found that Openness to Experience initially increases in stability with age, but becomes increasingly unstable around age 50. Likewise, individual levels of Openness to Experience displayed a similar pattern with age. That is, individuals up to the age of 30 were higher on Openness to Experience than older individuals. Moreover, level of Openness to Experience was found to decrease around age 60. Other research has found comparable results. For instance, Roberts and colleagues (2006) found that Openness to Experience increases from adolescence to adulthood, and then decreases in older age (i.e., late 50s and on). However, Srivastava and colleagues (2003) found a slightly different pattern. The authors observed a gradual decrease in Openness to Experience levels with age. Taken together, these findings suggest that, on average, individuals generally have higher levels of Openness to Experience when they are younger compared to older, and as such, this has implications for the intellectual investment theories.

As previously discussed, Openness to Experience, as an investment trait proxy, is theorized to influence how, where, and when individuals invest their cognitive ability under the intellectual investment framework (Ackerman, 1996; R. B. Cattell, 1971, 1987). Moreover, higher levels of Openness to Experience are thought to result in further growth and establishment of Gc and knowledge (Chamorro-Premuzic & Furnham, 2005; von Stumm et al., 2011). Based on the within-person changes in personality traits research, it follows that younger individuals, on average, will have higher levels of Openness to Experience, than older individuals, and as such, younger individuals will develop and strengthen crystallized-type abilities at a faster rate than older individuals. However, the empirical evidence examined Openness to Experience in the general population, not specifically in an organizational context. It is reasonable to assume that individuals within an organization do not fully represent the general population. Many reasons likely contribute to this notion. For example, organizations commonly select individuals to hire, some employees are terminated for poor performance, individuals leave for other organizations, employees retire at different times, and people self-select into particular organizations. For reasons such as these, a hypothesis about age-related differences in Openness to Experience is not fully justified.

Research Question 1: Do employees of different ages differ in their levels of Openness to Experience?

CHAPTER TWO

METHOD

Participants

Data were obtained from 382 organizational employees (e.g., managers, subordinates) who represented a variety of functional specialization areas within the organization (e.g., Accounting, Sales). All 382 employees had three consecutive years of job performance ratings (i.e., ratings from each of 2012, 2013, and 2014). However, two hundred ninety of these employees were removed from analyses because they were missing intelligence-assessment data and personality-assessment data (one employee was removed due to missing only intelligence-assessment data). The missing data were due to the organization transitioning from a paper-based database to an electronic database and as such, not all of the paper-based assessment information was electronically available at the time of data retrieval. Statistical test were used to compare the removed and retained employees to determine if differences between these two groups existed (see Appendices A and B for comparison between removed and retained employees). One statistically-significant difference was observed for sex; however, the intellectual-investment framework does not posit sex differences, so the differences observed do not hinder the study. Hence, the total sample for this study included 92 employees. The mean age of the employees was 41.93 years (*SD* = 10.13). The majority of the employees were male

($n = 59$, 64.10%). In addition, most of the employees were classified as White ($n = 71$, 77.20%), 19.60% as African American ($n = 18$), and 3.30% as Asian ($n = 3$). The mean organizational tenure of employees was 7.67 years ($SD = 4.78$).

Instruments

Gc

Employees completed the Watson-Glaser Critical Thinking Appraisal (WGCTA) designed by Watson and Glaser (1980). The WGCTA is a measure of Gc (verbal reasoning; Furnham, Dissou, Sloan, & Chamorro-Premuzic, 2007). The measure consists of five sub-domains: inferences (discriminating among degrees of truth about conclusions drawn from the given data), recognition of assumptions (understanding unstated suppositions in given assertions or statements), deduction (deciding whether particular conclusions necessarily follow the given information in statements), interpretation (evaluating evidence and determining if generalizations are justified given the data), and evaluation of arguments (discriminating between weak or irrelevant and strong or relevant arguments given a specific issue; Watson & Glaser, 1980). The five sub-tests contribute to the overall composite score of the WGCTA (Furnham et al., 2007). Each item has one correct answer and the maximum total composite score on the WGCTA is 40. For this study, the overall composite score (i.e., the total number of correct responses) was used for analyses. Psychometrically, the WGCTA was found to have an internal consistency of .83, test-retest reliability of .89, and a criterion-related (overall job performance) validity of .39 (Watson & Glaser, 2006). In addition, the WGCTA was found to correlate with a widely used cognitive ability test, the Wechsler Adult Intelligence Scale (WAIS), at .52 (Watson & Glaser, 2010).

Openness to Experience

Employees completed the Occupational Personality Questionnaire (OPQ32i) developed by SHL (1999). For purposes of this study, items from the OPQ32i were selected by an informed-judges approach to form the Openness to Experience measure used in the study. The OPQ32i measures 32 job-related personality traits (Bartram & Brown, 2005). The personality measure contains forced-choice items and consists of 104 quad sets. Sets of four statements (each relating to a different personality scale) are contained in each quad (Bartram, 2013). For all quads, employees endorse two of the four statements (one statement as "most like me" and the other as "least like me"). After completing, a score on each of the 32 personality ipsative scales is produced from a fixed number of points (i.e., 416) that are distributed among the scales (based on the statements endorsed). The Five-Factor Model (Costa & McCrae, 1992) and normative trait scores can be derived from the OPQ32i. Although it is important to note that factor-analytic evidence suggests that the OPQ32i is larger in scope than the Five-Factor Model, containing aspects of motivation (e.g., need for power, need for control) not typically included in personality-trait definitions in the Five-Factor Model (Bartram, 2013). Despite the larger scope, multidimensional IRT scoring methods have been developed to analyze the individual-choice patterns and from the patterns, Five-Factor normative trait scores can be derived (Bartram, 2013; SHL, 2009). Moreover, ipsative and normative scoring methods yield similar results, especially when the strict ipsative constraint (i.e., the use of all 32 scales) is removed (Baron, 1996; Bartram, 1996). In other words, the aggregation of only a subset of scales removes the constraint. Not surprisingly, of the 32 scale scores, only a subset (viz. 25) are aggregated to yield normative personality traits from the Five-Factor Model (Bartram, 2013).

The OPQ32i scales that combine to produce the personality trait Openness to Experience are Variety Seeking, Innovative, Conceptual, Behavioral, and Conventional (Bartram & Brown, 2005; Bartram, 2013). All of these scales are positively related to Openness to Experience, except for Conventional (negatively related). The test publisher retains the scale weights for the Five-Factor conversion equations, which are needed to create the IRT-derived composite score of Openness to Experience (SHL, 2006).The scale weights were unavailable from the test publisher because those weights are considered to be protected intellectual property. Due to this, an informed-judges approach was utilized to conceptually link OPQ items to Openness to Experience.

It was essential that items could be identified from the OPQ32i could be mapped to Openness to Experience (Aguinis & Edwards, 2014). This correspondence was evaluated by providing three informed judges (i.e., individuals with advance knowledge in psychometrics and personality theory) a list of OPQ items and asking them rate the extent to which each item is conceptually representative of each of the Five-Factor constructs. Informed judges were I-O doctoral students who completed graduate coursework in both personality and in advance psychometric theory and who also passed qualifying exams. For each Five-Factor construct definition (Costa & McCrae, 1992), judges rated the extent to which OPQ items represented that construct using a 5-point Likert-type scale (1 = *not at all*, 2 = *very little*, 3 = *somewhat*, 4 = *quite a bit*, 5 = *completely*). An average deviation (AD) index was calculated to assess the agreement among informed judges (Burke & Dunlap, 2002; LeBreton & Senter, 2008). Items for

Openness to Experience were retained if the AD index met or exceed 0.8 (signifying adequate levels of agreement for a 5-point scale; Burke & Dunlap, 2002), the mean ratings among the judges for the Openness to Experience construct were 3.5 or greater, and the mean ratings on the remaining Five-Factor constructs (i.e., Extraversion, Agreeableness, Conscientiousness, and Emotional Stability) were 3.4 or below (see Appendix C for ratings of retained items). Based on these ratings, four items representing Openness to Experience were retained. All employees in the sample had a rating from 1 to 5 (1 = *key limitation*, 2 = *likely limitation*, 3 = *moderate*, 4 = *likely strength*, 5 = *key strength*) on each of these OPQ items (e.g., describes themselves as a creative individual). These ratings map onto an extent scale (e.g., not like me, very much like me). For this study, these four items were summed to create a composite score for Openness to Experience (1 to 20 score range) and the composite score was used for analyses (the Openness to Experience composite score stemmed from the informed-judges approach, not from the IRT-derived scale weights from the test publisher). The internal-consistency reliability for the four items retained was .52. The low reliability is likely due to Cronbach's alpha being an inappropriate reliability measure for ipsative items because ipsative data violate the assumptions (e.g., independence of error) needed for Cronbach's alpha (Meade, 2004). Likewise, the four items are summed to create a manifest variable, which carries the assumption that the measure is a reliable representation of the intended construct (Cole & Preacher, 2014). These four items were theoretically linked to Openness to Experience by an informed-judges approach, which provided evidence of content validity and meeting the manifest-variable assumption. Thus, the low internal-consistency reliability obtained for the items does not hinder the study.

Overall Job Performance

Overall-job-performance ratings for each employee were collected once annually through employee performance reviews (supervisory performance ratings). The ratings employees obtain range from 1 ("poor performance") to 5 ("superior performance"), varying in half-point increments. Data collection of the overall-job-performance data spanned from 2012 through 2014. Thus, each employee had an overall-job-performance rating for 2012, 2013, and 2014. For this study, the overall-job-performance ratings were used for analyses.

Procedure

Archival data were provided to the researcher by a large telecommunications organization located in the Southeastern United States. Data from the organization's personnel records included intelligence-assessment data, personality-assessment data, overall-job-performance data, and demographic data (i.e., age, tenure, race, sex). The researcher and a human-resources representative removed (i.e., de-identified) all identifying information about the participants in the data prior to data analyses and participants were assigned a random participant code. The intelligence and personality data came from assessments previously administered by human-resources personnel as part of the process of staffing the organizational. Employee intelligence and personality data in the sample were only collected once for each employee; however, the exact time of data collection varied among employees. Specifically, intelligence and personality data were collected around the time each employee was hired, although some employees were assessed after being hired. However, information regarding the specific date each employee was assessed was not available to the researcher.

CHAPTER THREE

RESULTS

A preliminary exploratory analyses was conducted to assess univariate normality among the study variables. Of the seven variables, only two met the assumption of normality (i.e., Gc, Openness to Experience), while the remaining variables did not (i.e., Age, Tenure, JP 2012, JP 2013, JP 2014). See Table 1 for Shapiro-Wilk test of normality among study variables. From these statistics, the appropriate statistical test was (i.e., parametric or nonparametric) selected for each analysis. See, for reference, Table 2 for descriptive statistics and bivariate correlations between study variables.

Table 1

Shapiro-Wilk Test of Normality Among Study Variables

Variables	*SW*	*df*	*p*
Age	.952	92	.002
Tenure	.839	92	.001
Gc	.983	92	.276
Openness to Experience	.979	92	.136
JP 2012	.831	92	.001
JP 2013	.852	92	.001
JP 2014	.851	92	.001

Note: $N = 92$.

Table 2

Descriptive Statistics for and Bivariate Correlations Between Study Variables

Variables	Mean	*SD*	1	2	3	4	5	6	7
1. Age	41.93	10.13	-						
2. Tenure	7.67	4.78	.229*	-					
3. Gc	29.74	5.05	.352**	-.026	-				
4. Openness to Experience	10.50	2.49	-.052	-.175	.029	-			
5. JP 2012	3.44	0.78	.125	.138	-.018	.038	-		
6. JP 2013	3.30	0.82	-.074	.141	.008	.044	.262*	-	
7. JP 2014	3.28	0.82	.127	-.025	.199	.024	.277**	.313 **	-
Range			26-66	2-27	18-40	5-17	2-5.5	2-5.5	1.5-5.5
Possible Range			-	-	0-40	0-20	0-5.5	0-5.5	0-5.5

Note: $N = 92$. *$p < .05$. **$p < .01$. Two-tailed Spearman's rho used for all non-normally distributed variables (see Table 1). Two-tailed Pearson's *r* was only used for the correlation between three & four.

Hypothesis 1: Gc Model Fit

The Latent Growth Modeling (LGM) was used to examine whether Gc was positively associated with overall job performance over time. Specifically, model fit was assessed after adding Gc (a time-invariant covariate) as a predictor of a latent-variable intercept (representing initial job performance ratings) and slope (representing the rate of change in job performance ratings) that were fitted to the overall-job-performance data (Preacher, Wichman, MacCallum, & Briggs, 2008). As mentioned before, the total sample consisted of 92 employees, which is close to the often-preferred sample size of 100 (although there is no minimum sample-size requirement) for latent growth modeling

(Curran, Obeidat, & Losardo, 2010). Preliminary exploratory analyses indicated the assumption of multivariate normality was met (Mardia's coefficient = -.819, critical ratio = -.567, $p > .05$). In addition, there were no multivariate outliers in the data. Model fit was assessed with the chi-square test statistic (χ^2), comparative fit index (CFI), Tucker-Lewis index (TLI), root-mean-square error of approximation (RMSEA), and Akaike Information Criterion (AIC; Hair, Black, Babin, & Anderson, 2009; Preacher et al., 2008; Schermelleh-Engel, Moosbrugger, & Müller, 2003). For a model with fewer than 12 observed variables, cutoffs for good fit are as follows: a non-significant χ^2 value, a CFI value and a TLI value of .97 or better, and a RMSEA value below .08 (Hair et al., 2009). In addition, an AIC value was obtained for later comparison among models (Hooper, Coughlan, & Mullen, 2008; Schermelleh-Engel et al., 2003). After adding Gc to the model, the results indicated poor model fit, $\chi^2(7) = 17.930$, ($p = .012$); CFI = .188; TLI = .304; RMSEA = .131; AIC = 31.930. In addition, path weights from Gc to the intercept ($B = -.204$; $p = .186$) and slope ($B = .016$; $p = .174$) were both not significant. Thus, due to the poor model fit and the non-significant path weights, Hypothesis 1 was not supported.

Hypothesis 2: Age and Gc

The variables of age and Gc were examined to see if they met the assumption of normality. According to the Shapiro-Wilk test of normality, Gc ($SW = .983$, $df = 92$, $p = .276$) was normally distributed, but age ($SW = .952$, $df = 92$, $p = .002$) was not normally distributed. As a result, a nonparametric statistical test was used, Spearman's rho (r_s), to examine the association between age and Gc using the raw data (Howell, 2013). The results were statistically significant, $r_s(92) = .352$, $p = .001$ and in the appropriate direction (i.e., a positive correlation). As such, Hypothesis 2 was supported.

Hypothesis 3: Openness to Experience and Gc

As with Hypothesis 2, the variable of Openness to Experience was examined to determine whether it met the assumption of normality. According to the Shapiro-Wilk test of normality, both Gc ($SW = .983$, $df = 92$, $p = .276$) and Openness to Experience ($SW = .979$, $df = 92$, $p = .136$) were normally distributed. As a result, a parametric statistical test was used, Pearson's *r* (*r*), to examine the association between Openness to Experience and Gc (Tabachnick & Fidell, 2013). The results were not statistically significant, $r(92) = .029$, $p = .393$, and as such, Hypothesis 3 was not supported.

Hypothesis 4: Openness to Experience Model Fit

As in Hypothesis 1, the study used LGM to assess whether the relationship between Openness to Experience and overall job performance was moderated by job tenure. Both Openness to Experience and Tenure were standardized (see Frazier, Tix, & Barron, 2004 for a review on testing moderation) and added as predictors (time-invariant covariates) of the latent-variable intercept and slope. In addition, a two-way interaction term (the product of both standardized variables) was added as a predictor of the latent-variable intercept and slope (Frazier et al., 2004). Preliminary exploratory analyses indicated the assumption of multivariate normality was not met (Mardia's coefficient = 22.23, critical ratio = 10.88, $p < .05$). In addition, there were two multivariate outliers in the data (Mahalanobis distance values were significant at the $p < .001$) level. Removing these two outliers improved multivariate normality; however, the results of the LGM analysis without these outliers were not significantly different from the analysis with outliers. Therefore, they were kept in the analysis. The results indicated poor model fit, $\chi^2(9) = 16.932$, ($p = .050$); CFI = .217; TLI = -.305; RMSEA = .098; AIC = 52.932. Path weights from Openness to Experience to the intercept ($B = .664$; $p = .401$) and slope ($B = -.050$; $p = .414$) were both non-significant. Likewise, path weights from Tenure to the intercept ($B = .630$; $p = .437$) and slope ($B = -.046$; $p = .460$) were both non-significant. Similarly, path weights from the interaction term to the intercept ($B = .353$; $p = .671$) and slope ($B = -.027$; $p = .675$) were both non-significant. Thus, due to the poor model fit and the non-significant path weights, Hypothesis 4 was not supported.

Hypothesis 5: Gc and Openness to Experience Model Fit

As in Hypotheses 1 and 4, LGM was used to assess whether accounting for both Gc and Openness to Experience was positively associated with overall job performance over time. To this end, Gc and Openness to Experience were added as predictors (time-invariant covariates) of the latent-variable intercept and slope. Preliminary exploratory analyses indicated the assumption of multivariate normality was met (Mardia's coefficient = -1.416, critical ratio = -.812, $p > .05$). In addition, there were no multivariate outliers in the data. The results indicated poor model fit, $\chi^2(8) = 18.240$, ($p = .019$); CFI = .022; TLI = -.223; RMSEA = .119; AIC = 42.240. Path weights from Gc to the intercept ($B = -.207$; $p = .179$) and slope ($B = .016$; $p = .167$) were both non-significant. Likewise, path weights from Openness to Experience to the intercept ($B = .235$; $p = .450$) and slope ($B = -.018$; $p = .459$) were both non-significant. Due to the non-nested nature of the models, a ΔAIC was computed to compare models (Burnham, & Anderson, 2002). The ΔAIC values obtain when this model and the Hypothesis 4 model were compared to the

Hypothesis 1 model (the lowest AIC model) were 10.310 and 21.002, respectively. Both values were above three, which indicated that this model and the Hypothesis 4 model was not considerably better fitting than the Hypothesis 1 model (Burnham, & Anderson, 2002). To support Hypothesis 5, the model needed to have good fit, significant path weights, the lowest AIC value, and have both ΔAIC values three or greater (when compared to the previous two models). However, none of these were met and as such, Hypothesis 5 was not supported.

Research Question 1: Age and Openness to Experience

As mentioned in Hypotheses 2 and 3, Age, unlike Openness to Experience, is not normally distributed. Thus, a nonparametric statistical test (r_s) was used to examine the association between age and Openness to Experience (Howell, 2013). In particular, the study assessed whether the longitudinal evidence of age-related changes in Openness to Experience levels would be observed in an organizational context. That is, it was necessary to determine if employees in an organization would follow the same pattern that is observed in longitudinal studies of the general population (higher levels of Openness to Experience in people aged 30 and below and a slight decline in Openness to Experience levels in people aged 31 and above; e.g., Specht et al., 2011). To this end, the study examined whether employees aged 30 and below all had high levels of Openness to Experience and whether there was a slight negative decrease of Openness to Experience levels with age among employees aged 31 and above. First, the relationship among employees aged 30 and below ($N = 12$) was examined. The results were not statistically significant, $r_s(12) = .224$, $p = .242$. Second, the same relationship for employees aged 31 and above ($N = 80$) was examined. The results were not statistically significant, $r_s(80) =$ -

.081, p = .239. Furthermore, another nonparametric statistical test, Mann-Whitney U test, was used to examine whether mean differences existed between the two groups (Howell, 2013). The results were not statistically significant (U = 473.00, z = -0.82, p = .935). Though the data points available were not as robust as preferred, statistical tests were run on the limited data. Stemming from the aforementioned analyses, a picture of the pattern of Openness to Experience in the organization was observed. This pattern will be addressed in Chapter Four and how it departed from pattern observed in the longitudinal studies.

CHAPTER FOUR

DISCUSSION

The psychometric tradition of intelligence and Spearman's notion of *g* have largely prevailed as the dominant approach to intelligence used in I-O psychology, despite the fact that other approaches to intelligence exist. This is perplexing given that *g* is inadequate to explain either the growth or the decline of intelligence that occurs over the course of normal human development. Indeed, accumulating evidence suggests that *g* is an oversimplified model for explaining the development of cognitive abilities over time. That is, certain cognitive abilities (e.g., Gf) peak and begin declining in early human development, while others (e.g., Gc) generally increase throughout one's lifespan. Given this limitation to *g*, a more modern approach to intelligence was used that accounts for both the psychometric and developmental aspects of intelligence. Specifically, the work drew on the intellectual-investment framework due to its incorporation of normal cognitive development as well as its incorporation of personality traits thought to partially account for individual differences in cognitive abilities; incorporating these elements is thought to improve the prediction of job performance longitudinally. To this end several hypotheses were proposed and a research question to explore aspects of this framework in an organizational setting. Stemming from this study, a theoretical contribution as well as practical contributions were made.

Overall, most of the hypotheses were not supported, but a notable exception was observed. First, there was no positive association between Gc and job performance longitudinally. Given the accumulated evidence of intelligence's strong relationship with job performance, the failure to obtain support for the first model (Hypothesis 1) was quite troublesome. Moreover, a positive relationship between Gc and job performance was not observed for any time point (see Table 2). This finding was unexpected considering that conceptual link between Gc and the ability to acquire job knowledge. The job knowledge, in turn, was expected to be related to job performance. A number of limitations to this study likely contributed to this non-significant finding; however, the discussion of such limitations are saved for the limitation section because such limitations affect other findings as well. Second, no support was found for a positive association between Openness to Experience and job performance longitudinally (Hypothesis 4). This finding was, again, unexpected due to Openness to Experience's conceptual link to learning job knowledge, which is related to job performance. Indeed, even after accounting for the honeymoon effect, Openness to Experience was not positively associated with job performance. That is, the study accounted for tenure because Openness to Experience was expected to be more strongly related to job performance as tenure increased (i.e., honeymoon effect). However, the lack of support would be more worrisome if a more psychometrically-established measure of Openness to Experience was used (discussed in the limitation section). Third and perhaps not surprisingly (given the previous two models), no support was found for both Openness to Experience and Gc being positively associated with job performance longitudinally (Hypothesis 5). The lack of support for this hypothesis was quite damaging to the intellectual-investment framework for predicting job performance longitudinally. Indeed, this model should have had the best fit under the intellectual-investment framework due to the incorporation of Gc and Openness to Experience (an investment trait proxy) posited to partially account for individual differences in the development of Gc.

In addition to the model-fit hypotheses, other hypotheses and a research question using a different statistical procedure were examined. For Hypothesis 3, there was no support for the presence of a relationship between Openness to Experience and Gc. This finding was unexpected given the empirical evidence showing a positive relationship between Gc and Openness to Experience. Indeed, under the intellectual-investment framework, Openness to Experience should be related to Gc because from a theoretical perspective, Openness to Experience partially guides one's investment into further developing Gc. This finding would be more worrisome if a psychometrically-sound measure of Openness to Experience was used. Hypothesis 2 was the notable exception among the otherwise unsupported hypotheses. Indeed, the notion that Gc generally increases with age was supported. This finding is in line with theory and with other empirical studies. Moreover, this finding provides additional support to the idea of the WGCTA being largely a measure of Gc.

With regard to the research question, the study examined whether age-related differences in Openness to Experience levels existed in the sample. Specifically, longitudinal evidence suggests that Openness to Experience levels are higher for individuals aged 30 and below than the remaining age groups. Moreover, longitudinal evidence suggests that Openness to Experience gradually declines over one's lifespan. These longitudinal studies have typically examined changes to Openness to Experience levels in the general population. However, the study examined this phenomenon in an organizational context. As such, it was reasonable to expect that the organization's workforce would not fully represent the general population due to numerous reasons (e.g., organizations select individuals to hire and terminate poor performers). Though there was limited data, the same pattern in the sample as is expected in the general population was not observed. That is, the study did not find mean differences in Openness to Experience levels between individuals 30 and below and individuals 31 and above. Likewise, a gradual decline of Openness to Experience as age increased was not observed. In fact, there was no discernable pattern in the sample, which suggests that the organization did not have a fully-representative general-population sample. Taken together, these findings (both expected and unexpected) have theoretical and practical implications as well as provide future research directions.

A theoretical contribution was made to the intellectual-investment framework by integrating the contextualist perspective of personality and investment traits. That is, it is theorized that intellectual-investment traits are subject to change throughout one's life; however, due to the limitations of the study, theoretical contribution was not empirically supported. As such, future research is recommended to test this theoretical contribution by using a larger sample size and a psychometrically-sound measure of Openness to Experience in other organizational settings. This theoretical contribution is important to empirically investigate because intellectual-investment traits are defined as stable individual differences (von Stumm et al., 2011), yet the most frequently used proxy for investment traits is Openness to Experience, which is subject to ongoing change (e.g., Roberts et al., 2006; Specht et al., 2011). Indeed, longitudinal evidence points to younger individuals (aged 30 and below) having, on average, higher levels of Openness to Experience than the remaining age groups. Moreover, Openness to Experience levels have been found to gradually decrease with age. As such, theoretical age differences in investment trait levels likely result in differing rates of development of crystallized-type abilities. That is, younger individuals, on average, will acquire crystallized-type abilities at a faster rate than older individuals. Although Openness to Experience is a proxy for intellectual-investment traits, it stands to reason that intellectual-investment traits are subject to the contextualist view of continuous change throughout one's lifespan. Thus, this theoretical contribution provides an opportunity for researchers and future studies to improve job performance prediction.

Even though the findings did not support the intellectual-investment framework in an organizational setting, practical suggestions are discussed based on theory and other empirical findings. The intellectual-investment framework is believed to have the potential to improve our prediction of job performance over and above *g*. Indeed, intelligence is not the sole determinate of job performance and as such accounting for an additional factor (i.e., personality) will likely allow improved job performance prediction. Moreover, I-O psychology rarely examines the combination of personality and intelligence and as such, this framework provides a theoretical rationale for accounting for both. Thus, I-O practitioners can assess for both Gc and Openness to Experience when staffing an organization. Compared to the personality trait Conscientiousness, placing more or equal importance on Openness to Experience in staffing is a departure from the evidence contained in meta-analytic studies (e.g., Barrick et al., 2001; Woo et al., 2014). Yet, the intellectual-investment framework and the honeymoon effect suggest that Openness to Experience is an important predictor of job performance. Again, no support was found for Openness to Experience's importance in predicting job performance longitudinally, but given the assembled theoretical evidence, it is believed the best information would cause us to conclude that Openness to Experience needs to be accounted for in staffing decisions (Minbashian et al., 2013). To this end, future research should continue to investigate both Gc and Openness to Experience for use in predicting job performance longitudinally. That being said, improving job performance prediction is one benefit of this framework; however, other benefits exist.

Future research should investigate whether the intellectual-investment framework can improve diversity in an organization. Specifically, research evidence has shown that intelligence tests can result in large differences among racial groups (e.g., Roth, Bevier, Bobko, Switzer, & Tyler, 2001). These differences often lead to a lower selection rate for minorities and as such, adverse impact often occurs, which is prohibited by Title VII of the Civil Rights Act of 1964. However, under the intellectual-investment framework, crystallized-type abilities should not be viewed as static. That is, a score on a Gc test can be view simply as a snapshot of one's current Gc levels, not a non-changing ability. Coupling this normal human development of Gc with investment traits (e.g., Openness to Experience), I-O practitioners can lower cutoff scores for Gc in staffing. That is, two individuals can have the same Gc levels, but differ on Openness to Experience levels. In the context of staffing, these differences in Openness to Experience levels help account for differences in job-performance trajectories between these two Gc-identical individuals. Extending this notion forward, a racial-minority candidate with slightly-lower Gc but higher Openness to Experience could be selected over a racial-majority candidate with slightly-higher Gc but lower Openness to Experience because the racial-minority candidate will likely continue developing Gc at a faster rate than the racial-majority candidate and hence, in time, higher Gc levels should lead to higher job performance. That being said, an I-O practitioner or organization adopting this framework for staffing purposes must also consider the legal ramifications that could arise and the timeframe in which such an approach would be beneficial to the organization.

Age discrimination needs to be considered under this framework. In particular, the Age Discrimination in Employment Act (ADEA) of 1967 and as modified in 1986, prohibits the discrimination of employees aged 40 and over. This law has implications for the intellectual-investment framework. For example, two individuals could be equal in terms of Gc and Openness to Experience but differ in age (e.g., one individual being 25 and the other being 50). An I-O practitioner or organization may be tempted to select the 25-year-old candidate due to an expected increase in Openness to Experience levels to age 30 and/or (at the very least) a smaller decline of Openness to Experience over any given period of time. Thus, over time, the 25-year-old candidate is expected to obtain a higher level of Gc and develop Gc at a faster rate than will the 50-year old candidate. If an organization systematically selects employees based on these age-related changes in Openness to Experience and Gc, age discrimination is likely to occur. However, this framework can also help an organization avoid the legal ramifications of adverse impact. Hence, the implementation of this framework for staffing purposes must be accompanied by legal considerations.

Limitations and Future Directions

Although this study has made important contributions to the study of intelligence in the workplace, more empirical investigations must be undertaken to fully understand the intellectual-investment framework in an organizational context. Specifically, a number of limitations hindered the ability to find support for the majority of the hypotheses. First, a psychometrically-sound measure of Openness to Experience was not used in this study (The converse equations were unavailable from the test publisher needed to create a psychometrically-sound measure due to the equations being considered intellectual property). Indeed, an informed-judges approach was used to create an Openness to Experience composite score using items that stemmed from an ipsative measure. Second, the longitudinal data consisted of only three time points. Normal human development of crystallized-type abilities may not change enough over three years for any substantial differences to be observed. Indeed, detectable changes may result after time spans of 10, 20, or 30 years (Ackerman & Beier, 2012). That being said, this long-term view may not be appealing for organizations in industries that experience high levels of turnover among employees. Specifically, organizations in these industries may see the majority of their employees exit before the intellectual-investment framework is beneficial for staffing purposes. That is, not enough time will likely pass for individual differences in investment to account for differences in performance trajectories. Third, artifactual changes in reported performance data may have been responsible for ill-fitting models. The archival data came from an organization that was experiencing large-scale organizational change; during the years in which analyzed job-performance data were collected, the organization had acquired a few smaller organizations and had added these organizations' workforces to their own. Large-scale organizational change has been theorized to impact employees' cognitive and affective readiness for change, which have been considered antecedents of job performance (e.g., Rafferty, Jimmieson, & Armenakis, 2013); such impact may lead to decreases in reported performance. Indeed, there were statistically-significant declines in the mean job-performance ratings used in the study. A Friedman test indicated that differences in job-performance ratings existed ($\chi^2(2) = 11.362$, $p = .003$) and post-hoc analyses revealed a statistically-significant decline in job-performance ratings both from 2012 ($M = 3.44$) to 2013 ($M = 3.30$; $p = .036$) and from 2012 to 2014 ($M = 3.28$; $p = .008$; note that the Friedman test and its associated post-hoc analyses are non-parametric and based on rank orders; mean values are reported here for interpretability). Such interference with job-performance data outside of the confines of ordinary organizational functioning may have contributed to the lack of support found for many of the study's hypotheses. Fourth, the sample size used was adequate for LGM (Curran et al., 2010), but a larger sample size may help better evaluate the intellectual-investment framework in staffing. Fifth, the job-performance measure was a single item, which is likely less reliable in capturing performance changes when compared to multi-item measures. That is, a multi-item measure of performance may be more sensitive to capturing changes in performance over time. Nevertheless, single-item job-performance measures tend to correlate strongly with a similar multi-item measure of performance (e.g., Barrick & Mount, 1993; Cellar, Miller, Doverspike, & Klawsky, 1996). Moreover, the job-performance measure was a subjective rating from supervisors, so future research could incorporate single and multiple objective measures of job performance. Lastly, the sample was relatively homogenous (77.20% White). In addition, the mean age of employees was 41.93 years and the majority of the employees were male (64.10%), so future studies could incorporate a more-representative sample. Taken together, these limitations offer improvements that can be addressed in future studies.

Conclusions

Overall, no support was found for using the intellectual-investment framework in predicting job performance longitudinally. However, a number of limitations contributed to the lack of support and as such, researchers should conduct further empirical investigations of this framework in an effort to improve job-performance prediction. Furthermore, the study has made a theoretical contribution to this framework with regard to investment traits, which can be examined by researchers. Thus, although no support was found for the intellectual-investment framework in the study, researchers and organizations can use the intellectual-investment framework to improve their understanding of normal cognitive development that occurs in employees over time and how such change impacts job performance.

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APPENDIX A

MANN-WHITNEY U TEST FOR COMPARING RETAINED AND REMOVED EMPLOYEES

Mann–Whitney U Test for Comparing Retained and Removed Employees

Variables	N	Mean Rank	Sum of Ranks	U	z	p
Age						
Retained	92	208.52	19183.50	11774.50	-1.698	.09
Removed	290	186.10	53969.50			
Tenure						
Retained	92	192.88	17745.00	13213.00	-0.138	.89
Removed	290	191.06	55408.00			
Sex						
Retained	92	166.51	15319.00	11041.00	-2.877	.01
Removed	290	199.43	57834.00			
JP 2012						
Retained	92	197.04	18128.00	12830.00	-0.579	.56
Removed	290	189.74	55025.00			
JP 2013						
Retained	92	173.87	15996.00	11718.00	-1.810	.07
Removed	290	197.09	57157.00			
JP 2014						
Retained	92	198.85	18294.00	12664.00	-0.760	.45
Removed	290	189.17	54859.00			

Note: According to the Shapiro-Wilk test of normality, all variables did not meet the assumption of normality $p<.002$.

APPENDIX B

DEMOGRAPHIC INFORMATION BETWEEN RETAINED AND REMOVED EMPLOYEES

Demographic Information Between Retained and Removed Employees

Variables	*N*	%
Race		
White		
Retained	71	77.20
Removed	194	66.90
African-American		
Retained	18	19.60
Removed	91	31.70
Asian		
Retained	3	3.30
Removed	2	0.70
Sex		
Male		
Retained	59	64.10
Removed	136	46.90
Female		
Retained	33	35.90
Removed	154	53.10

APPENDIX C

INFORMED-JUDGES' RATINGS

Informed-Judges' Ratings

OPQ Items	AD Index	Openness to Experience	Extraversion	Agreeableness	Conscientiousness	Emotional Stability
Describes themselves as a creative individual	0.0	5.0	1.0	1.3	1.0	1.0
Questions traditional methods when generating ideas	0.0	5.0	1.3	2.3	2.0	1.3
Challenges the rules when implementing an idea	0.67	4.0	2.7	3.3	2.7	1.3
Ideas and solutions may lack intellectual depth	0.67	4.0	1.0	1.0	1.3	1.0

Note: Values for the Five-Factor constructs represent the mean ratings among the informed judges (N = 3). AD Index values represent the informed-judges' agreement for Openness to Experience.