ABSTRACT

Using Structural Equation Modeling to Examine the Relationships Between
Environmental Characteristics, Intrapersonal Characteristics,
and Adult Numeracy Achievement

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Quantitative literacy or numeracy skills are increasingly important at every level in a knowledge-based society. The purpose of this study was to investigate the relationships between numeracy achievement, environmental and intrapersonal characteristics. Although the sample for this study included 5,862 U.S. adults (aged 16-65) from the Program for International Assessment of Adult Competencies (PIAAC), the results were weighted to represent the population. According to descriptive statistics, significant differences were found for multiple variables. The top 10% were more likely to have a foreign-born father, higher levels of parent education, more books in their childhood home, more years of formal schooling, be employed, and earn more money. Individuals with the following characteristics were more likely to be in the high numeracy group: male, native-English speaking, White, age 25 to 34, very good to excellent health, and no learning disability. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were conducted on a new Adult Numeracy Achievement Model. The second-order Intrapersonal factor predicted numeracy achievement in the top 10%; however, the second-order Environmental factor did not. Intrapersonal characteristics with small indirect effects on numeracy achievement included gender, age, race, native language, learning disability, health, and participation in ongoing training or education outside of a degree program. Findings were used to support suggestions for future methodological and future numeracy research. Implications for parents, adults, educators, and policymakers are suggested which include greater emphasis on mathematical learning, understanding, and application at all levels including school, home, and workplace.

Using Structural Equation Modeling to Examine the Relationships Between Environmental Characteristics, Intrapersonal Characteristics, and Adult Numeracy Achievement

by

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A Dissertation

Approved by the Department of Educational Psychology

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Submitted to the Graduate Faculty of
Baylor University in Partial Fulfillment of the
Requirements for the Degree
of

Doctor of Philosophy

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ACKNOWLEDGMENTS

My heartfelt appreciation to Dr. Susan Johnsen for the immeasurable investment she has made in my life as a professor, advisor, personal mentor, and friend. I have been significantly blessed by her example, encouragement, and scholarly perspective.

I am very grateful to Dr. Tracey Sulak for the numerous ways she has come alongside me to make this dissertation a reality. Her wisdom and work ethic are inspiring, and I am deeply appreciative of her faithful friendship.

I am indebted to Dr. Janet Bagby's friendship and for the cheerleading role she has played in my teaching and scholarship. She faithfully models a passion for teaching at the highest level.

I am also grateful to Dr. Grant Morgan's statistical assistance and for the leadership he provides to the Department of Educational Psychology.

To my other readers, Dr. David Ryden and Dr. Carson Mencken, I am grateful for your scholarly insight and support of this project.

To the faculty and students in the Department of Educational Psychology at Baylor University, thank you for the life-giving experience of learning in such a growth mindset environment with such amazing people. Rachel Renbarger and Noah Padgett have been especially inspirational and helpful in the dissertation process.

All of you have left a lasting impression on my life and given me a model for how to do the same with others. Thank you.

Finally, I would like to express appreciation to the Institute of Education Sciences (IES), Educational Testing Service (ETS), and the AIR PIAAC Team for providing and sponsoring PIAAC training and conferences. This dissertation is proof that I have benefited greatly from the research that has been conducted and the platforms by which you have made it accessible.

DEDICATION

To my husband, Grant, for his faithful support and encouragement.
Being married to you is a greater blessing than I deserve.

To our children, Ashley, Austen, Christiana, and Cameron.
I am so thankful for each of you. You are my greatest joy.

To my future grandchildren, may you embrace learning at every opportunity.

To my mother who provided a strong foundation for life and helped me to love learning.

To my late father who modeled a return to school in midlife, who with his wife, Eddy, facilitated the writing process and demonstrated their belief in my ability to complete this dissertation with an early graduation gift of a MacBook.

To my Savior, Jesus, who because of His grace has provided abundant life
both on earth and eternally with Him in Heaven.

CHAPTER ONE

Introduction

Quantitative reasoning for individuals and economies has become increasingly important with the economic shift from an economy built on industry to one built on knowledge (Carnevale & Desrochers, 2003). Similarly, Condelli et al. (2006) argued that quantitative reasoning, also referred to as numeracy or quantitative literacy, is an indispensable skill for success in all aspects of adult life including one's family, occupation, and citizenship. Individuals with low numeracy skills collectively damage economies and are more likely to be unemployed, earn lower wages, and report poor health (Bynner & Parsons, 1997; National Numeracy, 2018; Parsons & Bynner, 2005). Coulombe, Tremblay, and Marchand (2004) argued that increasing workforce numeracy skills could lead to significantly higher GDP per person.

Unfortunately, the United States has been increasingly lagging behind other nations in numeracy and mathematical performance and needs to take actions to remain competitive in an international community. For example, on an international assessment that measured adults' numeracy skills, the average U.S. score was 12 points lower than the international average (257 compared to 269), resulting in a rank of 18 out of 22 countries (Rampey et al., 2016). The United States also had a smaller percentage of adults scoring at the highest proficiency levels (10% vs. 12%) and a larger percentage of adults performing at the lowest levels (28% vs. 19%) in numeracy compared to the average international performance distribution. More employed adults demonstrated the highest level of numeracy competence (12%) compared to 4% of unemployed adults or 6% of those out of the workforce. Research focusing on developing talents in specific academic fields based on national needs, such numerical/mathematical skills, is important and reflective of our present sociocultural environment (Subotnik, Olszewski-Kubilius, & Worrell, 2011). Examining characteristics of individuals who demonstrate the highest numerical skill may have educational, occupational, and economic implications.

Definition of Numeracy

Numeracy, as a construct, does not have a universally accepted definition (Gal, Van Groenestijn, Manly, Schmitt, & Tout, 2005). Terms that have been used include *quantitative literacy*, *quantitative reasoning*, and *mathematical literacy* (Condelli, 2006). Because of its personal and national importance, two international adult surveys utilized panels of experts to agree on an operational definition. The Adult Literacy and Life Skills Survey (ALL) indicates numeracy is, "The knowledge and skills required to effectively manage and respond to the mathematical demands of diverse situations" (Murray, Clermont, & Binkley, 2005, p. 151). The Program for the International Assessment of Adult Competencies (PIAAC) expanded the definition to "the ability to access, use, interpret, and communicate mathematical information and ideas, to engage in and manage mathematical demands of a range of situations in adult life" (OECD, 2012, p. 34). Numeracy, therefore, is the application of mathematical concepts that were typically learned in formal situations to real-world situations (Geiger, Goos, & Forgasz, 2015).

Models Describing Numeracy Skills Achievement

In spite of the evident need for a highly numerically literate society, theoretical models for characteristics associated with developing these skills in adults are virtually nonexistent in the literature. Only two tangentially related models were found. Goos, Geiger, and Dole's (2012) numeracy in the 21st-century model was designed to assist school teachers with planning and reflection. The four elements of their model highlight student dispositions (e.g., flexible, confident, willing to take risks), mathematical knowledge (e.g., problem solving, mathematical concepts and skills), tools (e.g., physical materials, representational, digital), and real-world contexts. The second model, proposed by Rothman and McMillan (2003), used Longitudinal Surveys of Australian Youth (LSAY) to test a model of the theoretical student and student characteristics theorized to influence literacy and numeracy school achievement. Rothman and McMillan theorized that background/student characteristics (e.g., gender, nationality, socioeconomic status, etc.) and school characteristics (e.g., perceived school quality, % ESL, M school-level SES) influenced numeracy achievement test scores in year 9. Neither model specifically describes the development of superior skills nor considers adult achievement. Furthermore, Goos et al.'s (2012) model was intended for primary and secondary educators and did not consider other contexts that might influence adult performance.

Gifted Theoretical Models

Theoretical models in gifted education do address the limitations of numeracy models. First, these theoretical models attempt to explain the processes and or components that coalesce to influence an individual's superior performance in a specific domain. Second, they are not limited to K-12 school factors or contexts. Third, the models may include, children, youth, and/or adults. Finally, individuals who are considered gifted include those who perform in the above average to very superior ranges (i.e., the top 10 to 15 percent) in one or more domains. Given the flexibility and inclusiveness of these models, characteristics of outstanding performance in numeracy will be examined using three different talent development models: Gagné's (1985, 2000, 2012) Differentiated Model of Giftedness and Talent (DMGT), Renzulli's (1978, 2005, 2011) three-ring conception of giftedness, and Tannenbaum's (1983, 2003) star-shaped model. These models include ability (above-average or the top 10%) as necessary.

While all of the models incorporate environmental influences that impact the talent development process, Gagné and Tannenbaum identify specifically family wealth/social class, influential people (e.g., parents, peers, mentors, teachers), schooling/provisions, and the milieu (encompassing physical, social, and cultural environment). Renzulli (1986) indicates that his three-ring conception is "embedded in a Houndstooth background that represents the interaction between personality and environmental factors that give rise to the three rings" (p. 256); however, he provides very little elaboration, if any, on these environmental factors.

Intrapersonal factors are shared between at least two of the models include physical/mental health, motivation/volition/task commitment, and learning/thinking approaches such as creativity, goal management, autonomy, interests/passions, and strategic approach behaviors. Renzulli's theory narrows the concept of motivation to task commitment, which is energy focused on a specific problem or performance area (GERRIC, 2005). In addition, Tannenbaum and Gagné, include the influence of chance as a potential catalyst for talent development (Miller, 2012).

All of the aforementioned theorists believe that giftedness/talent can be demonstrated in a wide variety of professional/career, academic, artistic, and performance domains. Gagné's DMGT incorporates specific domains where talent can be demonstrated and is the only one that theorizes causal rankings and causal directional assertions in the talent development process (e.g., environmental and intrapersonal influence the developmental processes) (Miller, 2012).

In terms of prevalence, Renzulli and Gagné take a more liberal perspective, considering the top 20% or the top 10% of individuals, respectively, as gifted or talented. Tannenbaum's model specifies a more elite performance to be considered gifted. Although none of the authors of the three aforementioned models claimed to only focus on the talent development process occurring in youth or possibly into early adulthood, the absence of references to factors that potentially impact outstanding adult performance such as postsecondary education and career/occupational investment is a gap in the models. Given this gap, research related to gifted adults was also examined.

Characteristics Associated with Adults Talented in Specific Academic Fields

In addition to cognitive ability, scholars have reported on various characteristics associated with gifted adults that typically fall into the environmental or intrapersonal categories. Environmental characteristics include participants' familial background such as parental education and social class as well as participants' education and occupational opportunities. Additionally, influential relationships such as marital/partner status and children are reported. Intrapersonal characteristics include biologically influenced factors such as gender, race, health, and disability as well as nonintellective characteristics such as motivation, perseverance, and approaches to learning.

Strong empirical research on gifted or high-performing adults in a specific academic field are rare (Rinn & Bishop, 2015). Studies on this population are primarily prospective or retrospective. Most of the research is conducted using adult participants who were labeled gifted in childhood or adolescence, typically on the basis of a standardized test score above a predetermined cutoff level or some other indication of potential. An implicit assumption of this prospective method is that gifted children will grow up to be gifted adults. Alternatively, retrospective research identifies eminent or high-performing adults and examines their lives in a rearview mirror by looking back to characteristics, events, and experiences in childhood and adolescence. For example, of the 60 empirical research studies identified by Rinn and Bishop's (2015) systematic review, only 10 studies selected participants based on adult accomplishment in a specific field, whereas most of the remaining studies examined the adult lives of those who had demonstrated potential or had been labeled as gifted in childhood.

Along with these 10 studies, other relevant literature on characteristics associated with high-performing adults was reviewed. Included in the review were empirical or seminal studies of high ability or gifted U.S. adults who were born during the second half of the 20th century. Reflective of the available pertinent literature, the vast majority of the studies used prospective samples who were identified as gifted youth and followed into adulthood. In only two studies were participants singularly selected based on adult performance – admission to a Ph.D. program (Lewis, Kitano, & Lynch, 1992) or an adult IQ score above 120 (Antshel et al., 2009). In addition, a subset of research on the Studies of Mathematically Precocious Youth (SMPY) included both participants who were selected as a result of their admittance to a top STEM graduate program as an adult and participants identified in youth (Lubinski & Benbow, 2006; Lubinski, Benbow, Shea, Eftekhari-Sanjani, & Halvorson, 2001; Lubinski, Benbow, Webb, & Bleske-Rechek, 2006).

Environmental Characteristics

Environmental characteristics associated with high performing adults include relationships and developmental provisions such as education and occupation. The literature reported on information such as the educational attainment and immigration status of participants' family of origin and participants' immediate family relationships as adults. Relative to education and careers, participants' postsecondary attainment, college majors, general occupation, and annual salary were also reported.

Family of origin. Gifted adults come from more advantaged childhood backgrounds, including more books/resources and higher-SES households (Campbell & Feng, 2010). Janos and Robinson (1985) reported that higher levels of parental income, education, and occupation were also associated with academic and intellectual skills. Likewise, the highest-performing adults were more likely to have parents with college or graduate degrees (Kaufmann, 1981; Terman, 1954). For example, participants' paternal education level predicted high achievers in science (Benbow & Arjmand, 1990). Interestingly, extremely high performers may descend from immigrant parents. For example, 21% to 30% of participants were an offspring of a foreign-born parent (Benbow & Arjmand, 1990; Lubinski et al., 2006).

Marriage/long-term relationships and children. Little is reported concerning relationship characteristics associated with high-achieving adults. Research suggests that the majority of high-ability adults reported being married or in long-term relationships, but it is difficult to compare relationship status between studies because some report only marriage relationships, some report divorce, and the studies occurred when participants were at different ages. For example, 72% to 81% of former mathematically precocious youth (SMPY) in their 30s were married or in long-term relationships (Benbow et al., 2000). Among former Presidential Scholars in their late 50s and early 60s, 91% were married or "in marriage-like relationships" relative to 71% of the comparable population based on educational attainment (Kaufmann & Matthews, 2012, p. 87).

Gifted adults typically have fewer children than the general population. Of those with children, gifted adults had smaller families compared to average-ability peers or the general same-aged population. For example, gifted adults were more likely to be childless, and high-ability women had significantly fewer children compared to same-age peers but much closer to women with graduate degrees (Lubinski et al., 2006). By the time they reached their early 30s, over 45% of the mathematically gifted students had children (Benbow et al., 2000).

Postsecondary education. Highly gifted adults were more likely to graduate from college and earn graduate degrees compared to the general population. Of those identified with exceptional mathematics ability, 85%-95% earned a bachelor's degree, 37%-58% earned a master's degree, and 23%-28% earned a doctoratal degree (Lubinski & Benbow, 2006; Wai, Lubinski, & Benbow, 2005).

Results on participants' selection of majors may be influenced by the initial participant selection criteria and by participants' gender. For those identified as mathematically gifted in youth, many (48%-56%) earned a degree in mathematics or sciences (Benbow et al., 2000). Within the sciences, women tended toward medical and biological science majors, and men tended toward engineering or inorganic science majors. According to Kaufmann (1981), former Presidential Scholars most frequently chose to major in humanities (25%), physical/biological science (25%), or social sciences (22%).

Occupation. The occupations and salaries of gifted individuals, especially for males, often reflected their high educational levels. Mathematically gifted SMPY participants were most often employed at age 33 as executives/administrators, computer or math scientists, engineers, medical doctors, or lawyers (Benbow et al., 2000). In their late 20s, the occupations most often cited by Presidential Scholars included college professors (20%), medical doctors (13%), and lawyers (9%) (Kaufmann, 1981). By their late 50s/early 60s, a majority of the Presidential Scholars reported employment in three occupational fields: education/training (31%), medical/healthcare (14%), or legal (14%) fields (Kaufmann & Matthews, 2012). Interestingly, across various studies of high ability women, approximately 10%-15% reported careers as homemakers (Benbow et al., 2000; Hansen & Hall, 1997; Perrone, Tschopp, Snyder, Boo, & Hyatt, 2010).

Annual salaries of participants varied and substantial sex differences in annual income were noted (Benbow et al., 2000; Kaufmann, 1981; Kaufmann & Matthews, 2012). Former Presidential Scholars reported their peak income during their career as under \$100,000 (35%), \$100,000 to \$249,000 (42%), or over \$250,000 (23%) (Kaufmann & Matthews, 2012). Women, however, were twice as likely to have earned peak incomes under \$100,000, and 2 times as many men earned peak incomes greater than \$250,000 per year compared to women.

Intrapersonal Characteristics

As alluded to previously, environmental characteristics typically include people and institutions that are external to the individual. In contrast, intrapersonal characteristics reflect the health, disability, and internal characteristics such as motivation, persistence, and approaches to thinking and learning that are unique to the individual.

Health. When questioned about satisfaction related to their health status, one-third of former Presidential Scholars were *very satisfied*, and only 21% of respondents were *very dissatisfied* to *neutral* in their late 50s/early 60s (Kaufmann & Matthews, 2012). On average, men were more satisfied with their health than women. Research regarding twice-exceptional adults' health is rare (Rinn & Bishop, 2015). With respect to an exceptionality, Antshel et al. (2009) found that high-IQ adults with ADHD self-reported poorer occupational functioning and outcomes.

Persistence and task commitment. These are very important to outstanding achievement. The amount and quality of intensive practice are associated with fundamental differences in outcomes, and even gifted individuals need a minimum of 10,000 hours or about 10 years of full-time investment in developing expertise (Ericsson & Charness, 1994; Ericsson, Krampe, & Tesch-Römer, 1993). Although former Presidential Scholars expected to reach high levels of achievement in adulthood, in retrospect, they learned that hard work, struggle, and perseverance were more necessary than they had expected (Kaufmann & Matthews, 2012). Excelling in one's career requires investment as well. Males identified as having the most potential in STEM fields in middle-school or graduate school invested well beyond 40-hours per week in their work and career development (Lubinski, Benbow, & Kell, 2014).

Approaches to thinking and learning. In addition to perceiving greater levels of internal motivation such as persistence and perseverance, participants enrolled in a PhD program also perceived they had greater cognitive versatility, including flexible thinking and idea generation, compared to their average-ability peers (Lewis et al., 1992). Graduate students in the sciences indicated higher investigative interests than their peer-aged talent search participants and a greater affinity for scientific undertakings (Lubinski et al., 2001).

Problem

In summary, a review of the existing research and the talent development theoretical models indicates a substantial gap in the literature. As most historical research on gifted adults followed high-potential youth into adulthood, there is a paucity of research that examines characteristics of highly-able adults, particularly related to numeracy. Accordingly, Rinn and Bishop (2015) concluded, “more research should be conducted on the current lives and experiences of gifted adults” (p. 226). Second, most adult participants were identified based on childhood potential on a test and not on adult performance. Third, although there is theoretical support for a broader conception of giftedness (e.g., top 10% to 15%), most the research has narrowly examined individuals with potential or performance at the very highest levels (e.g., the top .01% to 1% or eminent men and women).

Furthermore, weaknesses in the theoretical models of both numeracy and talent development have been highlighted. First, the numeracy models do not explicitly indicate characteristics associated with the highest performers and are more limited to K-12 education. Relative to talent development models, the talent development models have not been empirically tested with any population, let alone a nationally representative sample. Finally, the numeracy and talent development models do not include adult contexts and their relationship to high numeracy performance.

Significance of the Study

The present study contributes to the scholarship related to the development of numeracy in adults. Individuals were selected for inclusion based on their adult performance in a domain, not their achievement as a child or youth. Rather than relying on a convenience sample, which is typically utilized in gifted research, a nationally representative sample of adults was used. Furthermore, the proposed theoretical model includes shared characteristics from multiple talent development models and expands these models for adult application with the inclusion of occupation, higher education, and work culture components. In contrast to previous research on presumably the most mathematically talented adults (top 1%), this research examines characteristics associated with a broader group of high ability individuals (10%) as proposed by the majority of talent development models. Structural Equation Modeling is set forth as a way to extrapolate relative effects of environmental and intrapersonal characteristics on adult numeracy performance, and, therefore, may have both theoretical and practical implications for educators, policymakers, employers, and other leaders.

Purpose

The purpose of this study, therefore, is to test a new conceptual Adult Numeracy Achievement Model based on environmental and intrapersonal characteristics identified in talent development models using structural equation modeling (see Figure 1.1). By testing this model with both the individuals capable of performing in the top 10% and with the individuals performing below the 90th percentile in numeracy, we can discern if the model provides a better explanation for those demonstrating numeracy talent. The second goal is to discern the relative influence of characteristics beyond natural ability to examine potential areas for intervention.

Current Study

Participants in this research were selected on the basis of their high performance as adults. A broader threshold for performance criteria (e.g., top 10%) for selecting participants aligns with Gagné's and Renzulli's theoretical models. Specifically, adult participants demonstrating numeracy proficiency at the 90th percentile or higher were selected from the Program for the International Assessment of Adult Competencies (PIAAC), an international survey measuring cognitive and workplace skills necessary for individuals and the society to flourish in the 21st century economy (Goodman, Finnegan, Mohadjer, Krenzke, & Hogan, 2013). In the United States, a nationally representative stratified area probability sample was conducted to identify PIAAC participants, and this research will isolate participants who perform at the highest level with respect to numeracy. Specifically, the following research questions were examined:

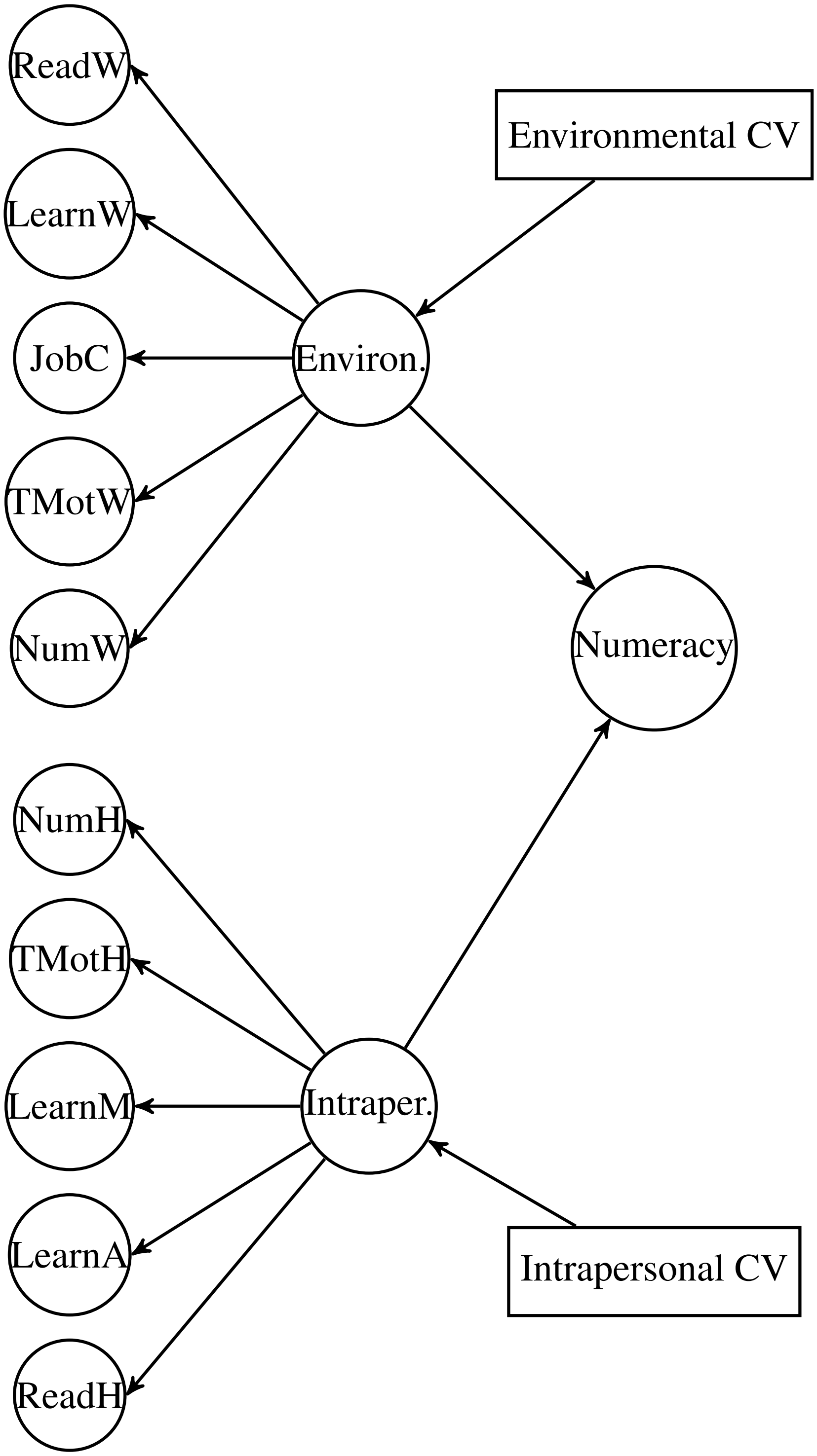

Figure 1.1. Adult Numeracy Achievement Model. Intrapersonal and environmental characteristics associated with numeracy proficiency.

1.0 What are the characteristics of U.S. adults who perform in the top 10% in numeracy proficiency?

  1.1 What are the environmental characteristics of U.S. adults who perform in the top 10% in numeracy proficiency?

  1.2 What are the intrapersonal characteristics of U.S. adults who perform in the top 10% in numeracy proficiency?

2.0 What are the characteristics of U.S. adults who perform below the 90th percentile in numeracy proficiency?

  2.1 What are the environmental characteristics of U.S. adults who perform below the 90th percentile in numeracy proficiency?

  2.2 What are the intrapersonal characteristics of U.S. adults who perform below the 90th percentile in numeracy proficiency?

3.0 To what extent do environmental characteristics and intrapersonal characteristics predict differences in numeracy proficiency for U. S. adults?

CHAPTER TWO

Literature Review

Importance of Numeracy

Numeracy skills are increasingly essential for individuals to be successful in various facets of adult life (Condelli et al., 2006). In fact, numerical knowledge and skills are “required to accommodate the mathematical demands of private and public life and to participate in society as informed, reflective, and contributing citizens” (Geiger et al., 2015, p. 531). In a knowledge-based economy, higher numeracy skills are associated with positive outcomes in the following areas: occupation, health-practices, income and finance, and community participation (Bynner & Parsons, 2006; Paulos, 2001). As a result of these and other similar findings, attention has been directed at operationally defining numeracy, defining numeracy, designing instruments to measure these skills, and developing an individual’s knowledge and skills in this area.

Definition of Numeracy

The term *numeracy* originated with the U.K.’s Ministry of Education (1959) *Crowther Report* regarding the state of education for youth aged 15 to 18. This word initially referred to one’s ability to understand scientific methods of study and to think quantitatively, representing “the mirror image of literacy” (p. 269). Since that time, other definitions and similar terms have burgeoned. Although the term numeracy is common, the United States frequently refers to the concept as *mathematical literacy* or *quantitative literacy* (Condelli et al., 2006; Geiger et al., 2015). Conceptions of numeracy, however, have evolved nationally and internationally, and the conception of numeracy underlying international assessments designed to measure mathematical literacy/numeracy has been gaining increased acceptance (Geiger et al., 2015).

Conceptions of Numeracy Used in International Assessments

At present, a universally accepted definition of numeracy does not exist (Condelli, 2006; Gal et al. 2005). Three international assessments, however, have operationally defined terms related to numeracy. One of the surveys, the Program for International Student Assessment, was designed for 15-year-old students. The other two assessments examined skills of adults: the Adult Literacy and Life Skills Survey and the Program for the International Assessment of Adult Competencies.

Program for International Student Assessment (PISA). The PISA measured student progress across multiple domains, including mathematical literacy, and has conducted assessments every three years since 2000. According to OECD (2017), the PISA relies on the following definition:

> Mathematical literacy is an individual's capacity to formulate, employ, and interpret mathematics in a variety of contexts. It includes reasoning mathematically and using mathematical concepts, procedures, facts and tools to describe, explain and predict phenomena. It assists individuals to recognize the role that mathematics plays in the world and to make well-founded judgments and decisions needed by constructive, engaged and reflective citizens (p. 67).

Adult Literacy and Life Skills (ALL) Survey. Conducted between 2003 and 2008, the ALL Survey defined numeracy as, "The knowledge and skills required to effectively manage and respond to the mathematical demands of diverse situations" (Murray et al., 2005, p. 151). However, an individual's numeracy ability is demonstrated by their responses to mathematical information in a given situation. These responses are influenced by one's knowledge base, reasoning processes, and characteristics, and, therefore, it is important to understand the underlying numerate behavior as conceptualized the ALL Survey;

> Numerate behavior is observed when people manage a situation or solve a problem in a real context; it involves responding to information about mathematical ideas that may be represented in a range of ways; it requires the activation of a range of enabling knowledge, factors, and processes. (Murray et al., 2005, p. 152).

The following survey maintained a level of compatibility with the ALL conception of numeracy as well as extended it to situate numeracy within the information age (PIAAC Numeracy Expert Group, 2009).

Program for the International Assessment of Adult Competencies (PIAAC). Slightly expanded compared to the definition of numeracy in the ALL Survey, the PIAAC definition incorporates the fundamental components shared by the various conceptualizations of numeracy across the literature (OECD, 2012). The PIAAC's definition of numeracy is "the ability to access, use, interpret, and communicate mathematical information and ideas, to engage in and manage mathematical demands of a range of situations in adult life" (OECD, 2012, p. 34). Using the word *engage* signifies the attitudes and beliefs that are coupled with cognitive skills to produce successful numerate outcomes. Specifically, the PIAAC numeracy proficiency was determined by participants' answers to authentic tasks embedded in culturally appropriate contexts that included working with and the interpretation of computations, percentages, measurements, application of simple formulas, and knowledge of basic statistics (OECD, 2012).

To better understand the PIAAC's broad construct of numeracy, the definition should also be paired with a more specific definition of numerate behavior (OECD, 2012; Rampey et al., 2016). Numerate behavior, according to PIAAC, "involves managing a situation or solving a problem in a real context, by responding to mathematical content/information/ideas represented in multiple ways" (OECD, 2012, p. 34). Figure 2.1 provides further expansion on the topic of numerate behavior. According to the PIAAC, numerate behavior encompasses four key facets: (a) context of numeracy use, (b) types of numerate responses, (c) mathematical content measured, and (d) mathematical representations (e.g., map, mathematical formula, graphs, tables, diagrams, etc.). Other processes facilitate the application of mathematical knowledge to decision making: conceptual understanding, problem-solving skills, literacy abilities, contextual understanding, previous experiences and practices related to numeracy, as well as individual beliefs/attitudes related to mathematics.

Numeracy Findings from Assessments

Results from the surveys previously described as well as findings from the National Assessment for Educational Progress (NAEP) indicate that the United States is not performing well compared to the U.S. desired proficiency levels or to other countries. Neither U.S. students nor U.S. adults appear to be prepared for the numeracy demands of adult life.

Student Results

Overall, our nation's future adults are not prepared for adult quantitative literacy demands. According to The Nation's Report Card (2017), only 34% of eighth-grade public school students demonstrated math proficiency (including 10% who scored at the *advanced* level) on the NAEP. Similarly, dismal results were found for U.S. 15-year-old students on the PISA. In 2015, the United States ranked 39 out of 70 participating nations with an average score of 470 on mathematics literacy, which was 20 points below the PISA international average (NCES, 2015a). Furthermore, only 5.9% of U.S. students performed at the highest levels (Level 5 & 6) relative to the international average of 10.7% (NCES, 2015b).

Numerate behaviour – key facets and their components

Numerate behaviour involves managing a situation or solving a problem…

1. In a real context:
- everyday life;
- work;
- society; and
- further learning.

2. By responding:
- identify, locate or access;
- act upon, use: order, count, estimate, compute, measure, model;
- interpret;
- evaluate/analyse; and
- communicate.

3. To mathematical content/information/ideas:
- quantity and number;
- dimension and shape;
- pattern, relationships, change; and
- data and chance.

4. Represented in multiple ways:
- objects and pictures;
- numbers and mathematical symbols;
- formulae;
- diagrams and maps, graphs, tables;
- texts; and
- technology-based displays.

5. Numerate behaviour is founded on the activation of several enabling factors and processes:
- mathematical knowledge and conceptual understanding;
- adaptive reasoning and mathematical problem-solving skills;
- literacy skills;
- beliefs and attitudes;
- numeracy-related practices and experience; and
- context/world knowledge.

Figure 2.1. PIAAC numerate behavior (adapted from OECD, 2012).

Adult Results

Numeracy performance on the adult surveys is not encouraging either. In terms of international rankings, the United States demonstrated a negative cohort change in numeracy, dropping one rank comparing the youth-aged PISA to the adult PIAAC ranking (Pensiero & Green, 2018). Out of six participating countries, the United States average score of 261 on the 2003 ALL Survey earned a rank of fifth place behind Bermuda, Canada, Norway, and Switzerland (Statistics Canada & OECD, 2005). Furthermore, only 12.7% of U.S. adults performed at the highest levels (Levels 4 & 5) compared to approximately 23% of adults in Switzerland, 18% in Norway, and 16% in Bermuda or Canada.

Although the PIAAC numeracy proficiency levels were scored very similarly to the ALL Survey, fewer U.S. adults scored at Levels 4 and 5 (10%) on the PIAAC (Rampey et al., 2016). The average U.S. numeracy score of 257 on the PIAAC was statistically significantly lower than 17 of the other 21 participating countries. Compared to the international average of 12%, fewer U.S. adults scored at the highest levels (10%).

PIAAC intrapersonal characteristics. The highest performers in numeracy, compared to the lowest performers (Level 0/1), were more likely to report good to excellent health, participate in volunteer activities, and report high levels of political efficacy (Tout & Gal, 2015). Numeracy scores also differed by race, gender, and age. More respondents who reported their race/ethnicity as White (12%) or Other (11%) scored at the top numeracy level (Level 4/5) than those who reported Hispanic (2%) or Black (1%) (Goodman et al., 2013). Men had higher numeracy scores with an average score of 265 compared to 250 for U.S. women, and this pattern was consistent in each age category and each educational attainment level (U. S. Department of Education, 2018). Across all PIAAC participating countries, average numeracy proficiency peaked around age 30 and gradually declined to age 65 (OECD, 2016a; Paccagnella, 2016). The United States generally followed the pattern but was the only country that demonstrated a small increase in average numeracy from middle-age (25-45) to maturity (age 45-65) (Paccagnella, 2016). Furthermore, the most highly numerate adults that show the least age-related declines in numeracy (OECD, 2016a). Compared to the other nations, however, the United States had the largest span between the numeracy scores of the top 10% and the bottom 10% of adults at age 45-65 reflecting increasingly different developmental trajectories.

PIAAC environmental characteristics. For the highest performing U.S. adults, there is an association between numeracy performance and increasing levels of education, employment, and wages. For example, the percentage of U.S. adults scoring at the highest numeracy levels decreases by level of education: 29% of individuals with a graduate or professional degree, 18% of those with a bachelor's degree, 8% with an associate's degree, 4% with a high school credential, and 8% who did not complete high school (Goodman et al., 2013). Twelve percent of U.S. employed adults, 6% of those out of the labor force, and only 4% of unemployed adults scored at the highest numeracy levels (Rampey et al., 2016). Of those top-performing adults who were unemployed, White adults (7%) were more likely to be unemployed than Hispanic (2%) or Black (1%) adults. Of the highest-performing adults who were unemployed, a larger percentage of those with a bachelor's degree (13%) were unemployed compared to those with an associate's degree (2%) or high school credential 1%). Relative to the lowest performers in numeracy (Level 0/1), the highest performers (Level 4/5) were more likely to be employed and earn high wages (Tout & Gal, 2015). In fact, every standard deviation (52.6 points) in numeracy proficiency was associated with a 12% increase in wages, even when other factors such as education, gender, and immigrant status are taken into account (OECD, 2013b). High numeracy skills was a stronger predictor than high literacy for employment and high wages (Tout & Gal, 2015).

In order to more deeply examine the characteristics associated with high performance in numeracy, theoretical models related to numeracy development were examined.

Models Related to the Development of Numeracy

Surprisingly, very few theoretical models exist related to the development of numeracy. This section will provide an overview of three models that were tangentially related to numeracy development and their application. The first model/framework is used to compare various numeracy conceptions. The second model theorizes a relationship between characteristics and numeracy in children, and the third model is primarily used for curriculum review and teacher development.

Continuum of Adult Numeracy Conceptions Framework

As conceptions of numeracy are inconsistent across countries and assessments, Maguire and O'Donoghue (2003) proposed a framework for comparing the various conceptions of adult numeracy on a continuum (see Figure 2.2). In the formative development phase, numeracy is equated with basic arithmetic. Although the "whole set of mathematics" is considered part of numeracy Mathematical Phase 2, not until the upper end of this phase is mathematics emphasized as important to daily life and made relevant. The culminating integrative phase reflects the largest jump in the sophistication wherein numeracy is conceived of as “a complex multifaceted sophisticated construct incorporating the mathematics, cultural, social, emotional and personal aspects of each individual in a particular context” (Maguire & O'Donoghue, 2003, p. 156). According to the researchers, the model was purposely left open for future additions as the domain matures.

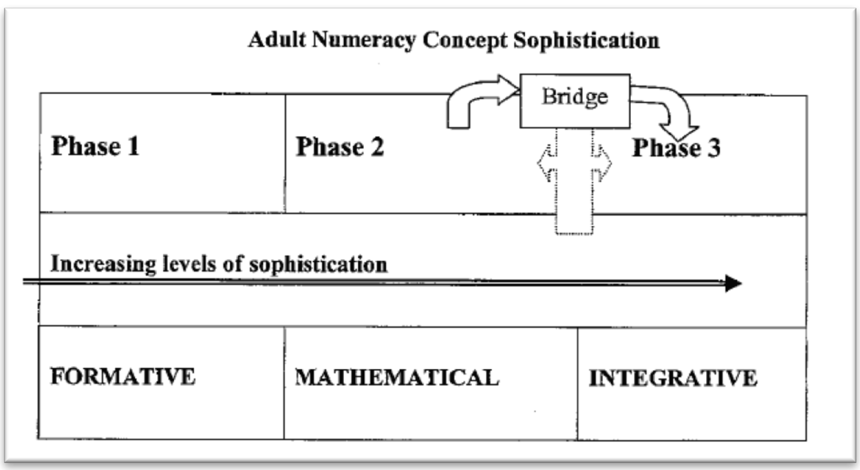

Figure 2.2. A continuum of development of the concept of numeracy (from Maguire & O'Donoghue, 2003).

Application of the model. Maguire and O'Donoghue (2003) used their framework to situate various conceptions of numeracy. Because of the wide range of mathematical skills assessed, the context of the items, and the problem solving required, numeracy, as measured by the ALL Survey, was placed within the integrative phase. With respect to the conceptualization of numeracy in the United States in the early 2000s, the authors situated the country in the middle of the mathematical phase (i.e., Phase 2). One reason for this placement is that numeracy was a relatively new term in the United States

(Maguire & O'Donoghue, 2003; Tout & Schmitt, 2002). Another reason was the presence of conflicting conceptualizations between documents such as the standards developed by the National Council of Teacher and Mathematics (2000) and the National Reporting Standards for Adult Education. Progress in U.S. numeracy conceptualization has been made. For example, members of the PIAAC Numeracy Expert Group included several researchers cited previously in the definition and conceptions section (e.g., Gal, Maguire, Tout).

Student Numeracy Achievement Model

In order to examine (a) variables related to differences in numeracy, (b) the amount of variation attributed to between-student differences and between-school differences, and (c) the overall amount of numeracy variance explained by the student and school levels, Rothman and McMillan (2003) constructed a model of factors influencing student achievement. Figure 2.3 presents their theoretical model, and Figure 2.4 presents their operational model. Using data from the Longitudinal Surveys of Australian Youth (LSAY), the researchers tested their model using hierarchical linear modeling.

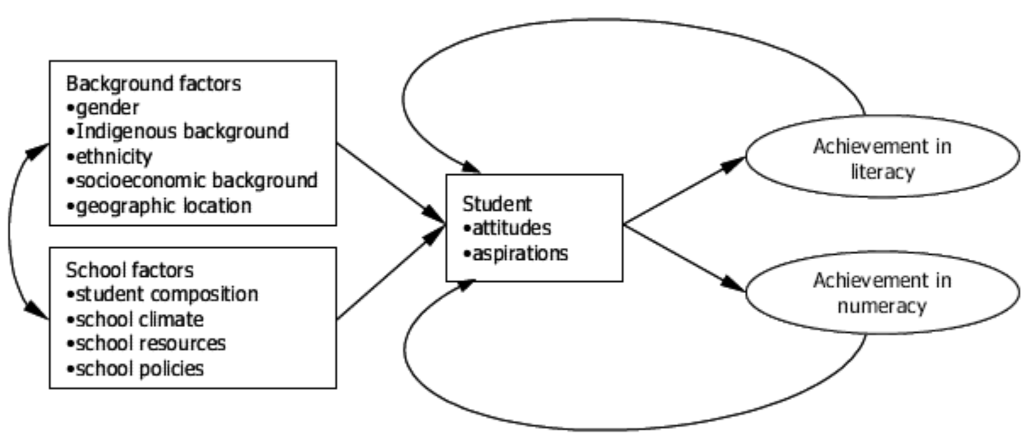

Figure 2.3. A theoretical model of factors influencing numeracy and literacy school achievement (from Rothman & McMillan, 2003).

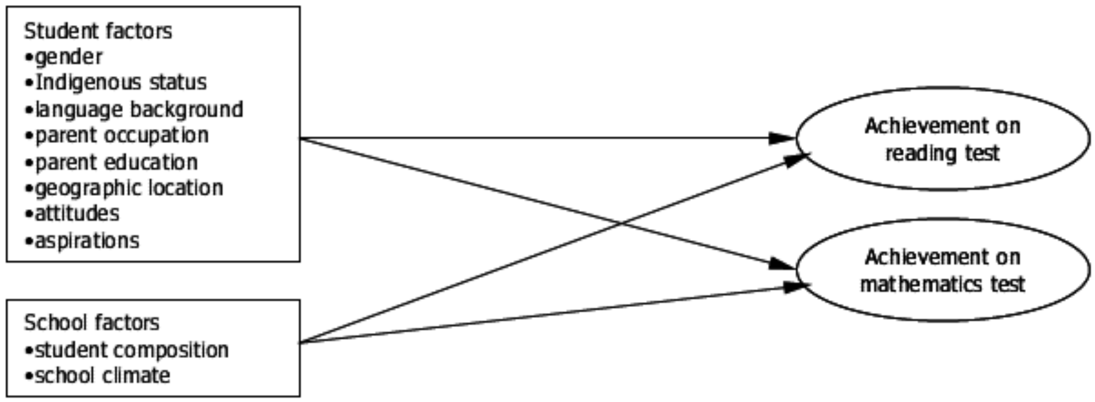

Figure 2.4. LSAY model of factors influencing numeracy and literacy school achievement (from Rothman & McMillan, 2003).

Application of the model. According to LSAY research, characteristics that contributed to numeracy achievement in grade 9 included individual and school differences (Rothman & McMillan, 2003). With respect to individual backgrounds, significant positive effects were found for gender, socioeconomic status, perceived quality of school life, plans to complete grade 12, and plans to attend college. Mother's education level, father's education level, and non-English language backgrounds were not significant. With respect to school-level differences, depending on the cohort, 82%-85% of the variance was explained by differences between the students within schools and 15%-18% of the variance was explained by differences between the schools. A majority (58%-65%) of the between-school variance could be explained by the variance within-schools. For example, the mean socioeconomic status of the school had the greatest impact, but the percent of English as a second language students and the overall school-level quality also had significant effects. Personal variables explained only 10%-11% of the within-school variance.

21st Century Numeracy Model

Although created to assist school teachers with lesson planning and reflection, Goos' (2007) 21st-century numeracy model was designed to incorporate current conceptions of numeracy as mathematical "knowledge-in-action" (Geiger, Goos, & Dole, 2011, p. 298; Goos et al., 2012). This tetrahedron-shaped model highlights the four necessary elements embedded within a critical orientation: dispositions, tools, math knowledge, and context (see Figure 2.5). Dispositions represent the students' willingness, flexibility, and perceived self-efficacy to use mathematics to engage real-world. Physical or digital tools used to facilitate and structure thinking include such items as models, measuring devices, graphs, drawings, diagrams, tables, maps, computer/software, internet, and calculators. Mathematical knowledge represents problem-solving

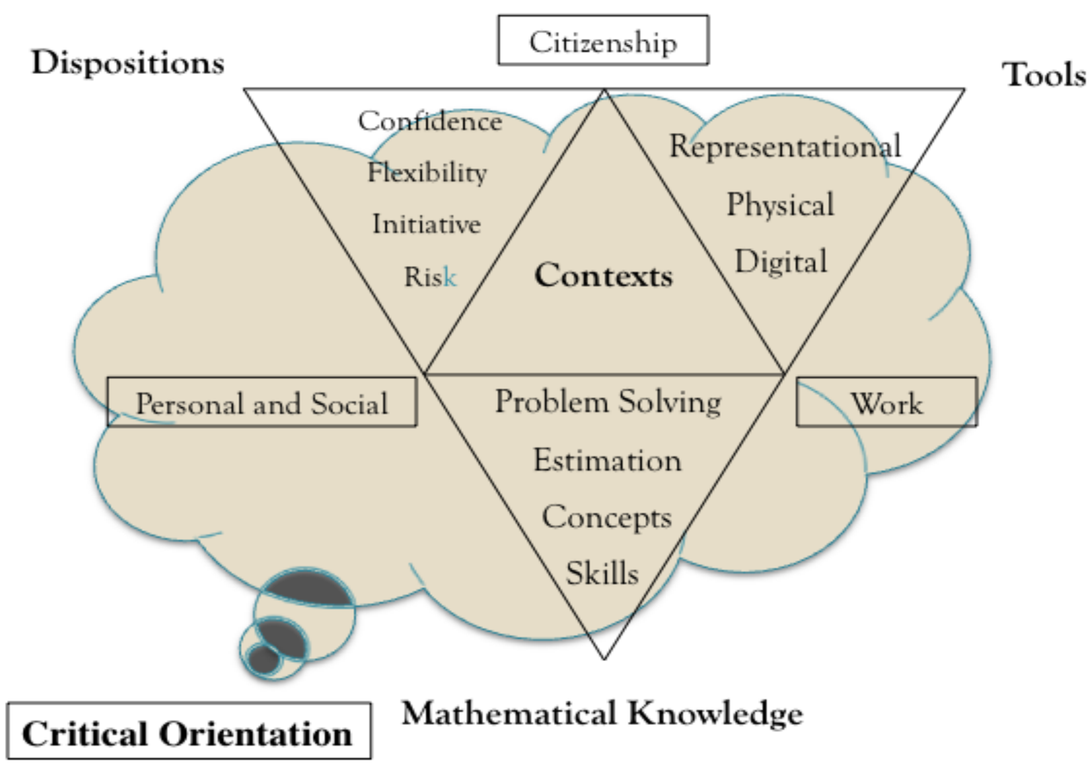

Figure 2.5. 21st-century numeracy (Goos, 2007; Goos, Geiger, & Dole, 2012)

approaches, estimation abilities, and understanding of mathematical concepts. In the center, knowledge-in-action is demonstrated both within real-life and school contexts. The backdrop, critical orientation, addresses how judgments and decisions are informed by mathematical information and represents how numeracy can be used for sharing, manipulating, or persuading others about various social or political issues.

Application of the model. As mentioned, this model was developed primarily for primary and secondary educators. The model has been used to audit middle-school curriculum and standards (Goos, Geiger, & Dole, 2010). Professional development was framed using the model, and primary and secondary teachers examined classroom activities and mapped their personal progress in numeracy using the model (Geiger et al., 2011). Research also demonstrated that using the model helped a teacher reflect on her growing understanding of numeracy, changed her teaching practices, increased her experimentation with tools in the classroom, and promoted a critical orientation in the classroom (Goos et al., 2012).

Summary

None of the three numeracy models is especially helpful in examining characteristics associated with high adult numeracy performance. Although Rothman and McMillan’s (2003) model provides a framework for examining characteristics associated with high numeracy performance, their model was designed for youth performance only and did not incorporate adult-level variables. Maguire and O'Donoghue’s (2003) framework is primarily helpful in examining the construct of numeracy. As Goos et al.'s (2012) model was intended for primary and secondary educators, it did not consider other contexts that might influence adult performance. In conclusion, none of the models specifically describe characteristics of adults who achieve in numeracy or those areas that contribute to the development of their superior knowledge and skills.

Models Related to the Development of Talent

Talent development models from the field of gifted education do address the limitations of numeracy models. Three theoretical models related to talent development are presented in order of their initial publication: Renzulli's (1978) Three-Ring Model, Tannenbaum's (1983) Star-Shape Model, and Gagné's (1985) Differentiated Model of Giftedness and Talent. Renzulli's model was based on highly creative/productive adults, and Tannenbaum's model was centered on the characteristics of highly-able youth. Table 2.1 provides a comparison of the models. Similar to the section on numeracy models, this section will provide an overview of each talent development model and then describe research related to the applications of the model.

Renzulli's Three-Ring Model

Renzulli examined the lives of highly accomplished/creative adults to identify characteristics that contributed to this performance. Based on this research, Renzulli's (1978, 2005, 2011) three-ring conception of giftedness highlighted three interactive clusters of traits necessary for outstanding accomplishment: creativity, task commitment, and ability (see Figure 2.6). He chose the Venn diagram to portray the dynamic state of the three clusters of traits, meaning the size of each cluster can vary over time (Renzulli, 1999). Renzulli posited that possession of one of these traits alone is not sufficient.

Table 2.1

Comparison of Three Talent Development Models

	Renzulli's Three-Ring Model	Tannenbaum's Star-Shape Model	*Gagné's DMGT 2.0*
Based on research of	• Highly accom-plished adults	• Highly-able youth	• Not clear
# of primary elements	• Three	• Five	• Four
All elements necessary	• Yes	• Yes	• Not specified
Directional assertions	• No	• No	• Yes
Desired outcome	• Creative-productive accomplishment in general or specific areas.	• Exemplary performer or producer in a field valued by humanity	• Demonstration of talent in a field (top 10%)
Ability	• Above-average in general ability and domain-specific ability	• Superior general intellect and special aptitude	• Natural abilities (top 10% in a domain)
Motivation	• Task commitment	• Nonintellective-Motivation	• Intrapersonal catalysts- motivation & volition
Intrapersonal traits that do not directly overlap	• Mental/physical energy • Optimism • Courage • Sensitivity • Vision • Romance with a discipline	• Mental health • Idiosyncrasies • Meta-learning • Approach behaviors • Self-concept	• Mental traits • Physical traits • Awareness • Volition
Environmental	• Note[1]	• Stimulating home • Stimulating school • Stimulating community • American culture	• Milieu • Provisions • Individuals
Creativity	• Creativity as essential element	• Creativity embedded in nonintellective	• Creativity as a natural ability/gift
Chance	• No	• Yes	• Yes

Note. [1]Environment represented by Houndstooth background but is not specified.

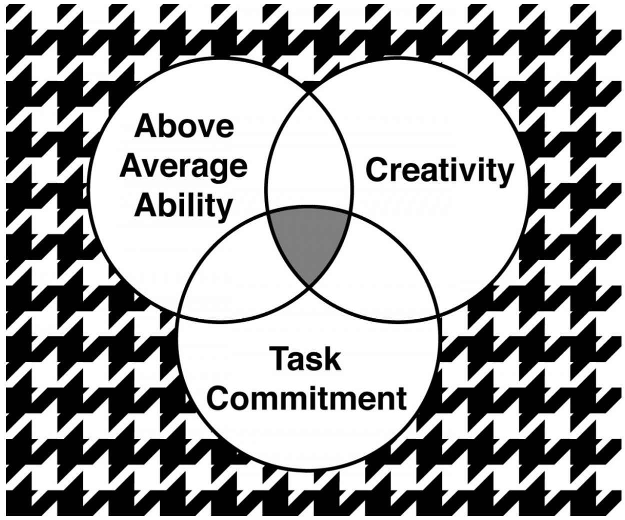

Figure 2.6. Renzulli's (1990) Three-Ring Model.

The individual needs to possess at least above-average ability that combines with high levels of both creativity and task commitment to demonstrate giftedness (the shaded intersection on the model). Renzulli (2005) considers above-average ability as capable of performance or possessing potential for performance in the top 15% to 20% in "any given area of human endeavor" (p. 260). Creativity, the second cluster of traits, includes divergent thinking, convergent thinking, originality, etc. Task commitment refers to a focused motivation, high level of commitment, perseverance, dedicated practice, and/or hard work invested in a domain of interest. Although the model includes a Houndstooth background (see Figure 2.7) intended to represent the interaction of "personality and environmental factors that give rise to the three rings" (Renzulli, 2005, p. 256), minimal additional description of the environmental factors is provided. Renzulli (1999), however, shared his regrets for not examining underlying environmental and personality dimensions in greater detail concluding that the addition of these characteristics holds the greatest promise for the development of the three-ring model. Since then, the model has been refined to include the addition of six co-cognitive items (see Figure 2.7) that interact with and augment one’s creativity, task commitment, and ability to enrich the developmental process: mental/physical energy, optimism, courage, sensitivity, vision, and romance with a discipline (Renzulli, 2005). The addition of bidirectional arrows represents multiple potential directions of these effects.

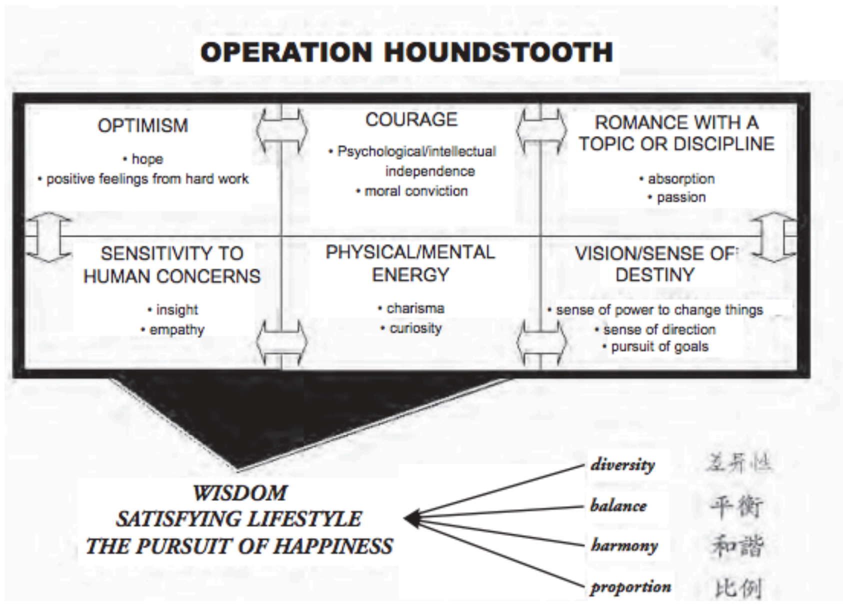

Figure 2.7. Operation Houndstooth model (Renzulli, Koehler, & Fogarty, 2006).

Application of the model. With elementary school students, gifted identification practices based on the three-ring model were examined (Reis & Renzulli, 1982). In this study, a product assessment form was used to score the students’ products from those with the highest intelligence/test scores (95th percentile) to those with above-average intelligence/test scores (80th -94th percentile). Given no significant differences between the group product scores, these data supported the identification of a broader percentage of students compared to traditional identification measures. As an outgrowth of the identification and development of children with talents for creative productivity, the Schoolwide Enrichment Model was developed. Numerous studies have examined various aspects related to the Schoolwide Enrichment Triad Model including model efficacy, learning styles, underserved populations, self-efficacy, curriculum compacting, and creative production (Reis & Renzulli, 2003; Renzulli & Reis, 1994). Given that this model is an "implicit-theoretical approach," Jarrell and Borland (1990), however, indicated that the three-ring model was implicitly theoretical and, therefore, could not be tested empirically (Sternberg & Davidson, 1986).

Tannenbaum's Star-Shaped Model

Less than a decade after Renzulli's three-ring model, Tannenbaum (1983, 2003) proposed a star-shaped model of giftedness to describe the process of developing talent to become an exemplary performer or producer in a domain that enhances humanity. Grounded by educational and psychological research on the characteristics of gifted children and adolescents, this model outlined five components that coalesce to enhance the talent development process: general ability/intelligence, unique domain-specific ability, psychosocial capabilities, environmental supports, and chance (see Figure 2.8). Tannenbaum asserts that a threshold level of general ability (i.e., intelligence) is necessary, but the amount of general ability needed depends on the specific domain. Specific aptitude is exceptional capacities/capabilities in a domain respected by society. Nonintellective factors encompass personal characteristics such as dedication and a willingness to exhibit short-term sacrifice to excel in the long-term. As talent is emerging in a child, the environmental supports include the individual's family, peers, educational experiences, as well as institutions and cultural values. Tannenbaum was the first to include the chance element in emerging talent as unpredictable events or unexpected circumstances in the individual or the environment, which may open, facilitate, or close avenues of exploration, and become integral to the developmental process. Depending on the domain, the necessary combinations of the five components may vary, but the integration of all five characteristics is necessary to maximize an individual's potential and to produce demonstrated giftedness in a domain. Conversely, a lack of one or more of these components serves to hinder emerging talent. Tannenbaum (1983), however, acknowledges that these factors "defy precise measurement because we have to rely on test instruments that lack validity and reliability" (p. 89).

Application of the model. Tannenbaum (1983, 2003) did not report any research applying this model, nor were any studies found during the literature review that tested his model. Also, similar to criticisms of Renzulli's model, Tannenbaum's model was also considered an implicit-theoretical model by Sternberg and Davidson (1986) and therefore is not empirically testable.

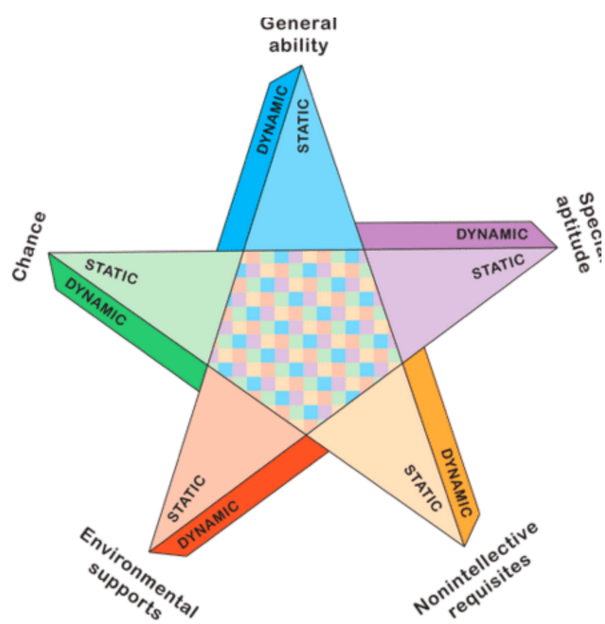

Figure 2.8. Tannenbaum's star-shaped model.

Gagné's Differentiated Model of Giftedness and Talent

Only two years after Tannenbaum's model, Gagné's (1985) Differentiated Model of Giftedness and Talent (DMGT) conceptualized talent development as a process in which gifts are progressively transformed to observable talents. This initial model and the subsequent DMGT 2.0 incorporated emerging potential (often associated with identification in youth) and realized achievement (the manifestation of adult giftedness), talent, into one theory (Gagné, 1985, 2000, 2012; see Figure 2.9). The term *gifts* in the DMGT model represented the top 10% of natural aptitudes in one domain compared to similarly-aged peers, whereas the term *talents* indicated the realized outcome of demonstrated competencies within the top 10% compared to individuals within the given field. Talents can be demonstrated in nine different fields. Six of these fields parallel American College Testing's World of Work occupational classifications, which are identified in parentheses: technical (realistic), science and technology (investigative), arts (artistic), social service, administration/sales (enterprising) and business operations (conventional). Three other areas for demonstrating talent include academic, games, and sports/athletics. Gagné did not believe that all individuals who possess high natural abilities (gifts) will demonstrate talent/adult achievement but asserted that all demonstrations of talent in adulthood require earlier giftedness (or close to the minimum 10% threshold).

Intrapersonal catalysts and environmental catalysts positively or negatively impact talent development depending on their presence or absence. Intrapersonal catalysts include physical, personality, and goal-management traits. Cultural and familial influences, as well as significant persons (e.g., family, teachers, role models, mentors),

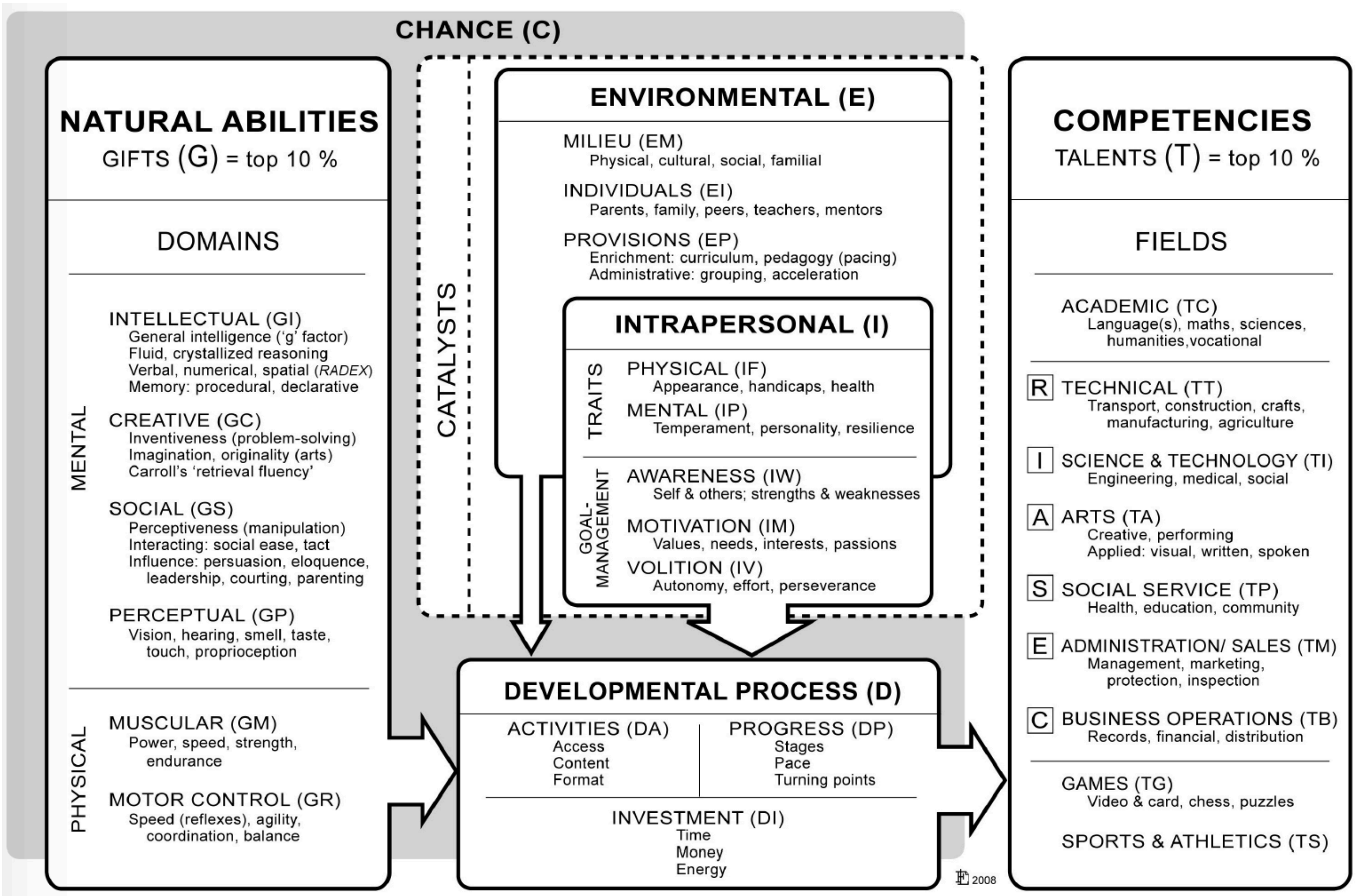

Figure 2.9. Gagné's (2012, 2013) Differentiated Model of Giftedness and Talent 2.0.

are specified environmental catalysts. The developmental processes include investment (e.g., time, money, energy), progress (pace and turning points) and access to activities that provide systematic development of aptitude. In the model's background, chance qualifies the developmental process as well as the environmental and intrapersonal. Gagné asserted that the intensity and continuity of the four casual catalysts (gifts, environmental, intrapersonal, and developmental processes) are individualized and dynamic in each person's talent development process.

Gagné (2012) differentiates between gifted and talented. To him, a gifted individual is one who possesses natural potential/aptitude in a domain placing him or her in the top 10% compared to similarly-aged peers, whereas a talented person is one who exhibits developed abilities demonstrating achievement or competency in the top 10% compared to peers in the field.

Compared to many prevailing criteria of giftedness (Terman's top 1%, Nauta & Corten's top 2%, SMPY's top 1%), Gagné's model also reflects a broader conceptualization of giftedness and talent with a minimum threshold of the top 10% of the relevant population (in a given domain). Gagné's (2012) DMGT model emphasizes "the presence of talented individuals in most human occupations" (p. 2) and does not require the attainment of eminence. He does, however, acknowledge differing levels of gifts/talents based on metric-based progressively selective subgroups: mild (top 10%), moderate (top 1%), high (top 0.1%), exceptional (0.01%), and extreme/profound (0.001%). Given that various talent domains are not highly correlated (e.g., technical and arts), by implication, the total number of talented individuals may significantly exceed 10% of the population.

Application of the model. Few empirical studies directly applied the DMGT model. Using retrospective questionnaires, Australian high-performance athletes responses supported intrapersonal catalysts (e.g., high commitment, perseverance, passion, and resilience), environmental catalysts (e.g., quality coaches, parental support), and chance events (Gulbin, Oldenziel, Weissensteiner, & Gagné, 2010). Using the DMGT framework, Gagné (1999) concluded that intrapersonal and environmental catalysts alone could not explain differences between the performance of average and expert young musical students, arguing that musical aptitude was largely responsible for differences that Sloboda and Howe (1991) found. Gagné (2004) reviewed talent literature and prioritized the components of his model in order of the highest influence to the smallest influence: chance, natural abilities/gifts, intrapersonal catalysts, developmental process, and environmental catalysts.

Summary

In summary, Renzulli, Tannenbaum, and Gagné all indicate that giftedness/talent may be manifest in a variety of domains. Although their models can apply to children, adolescent, or adults, the research base differs. Renzulli's model examined highly-accomplished adults, Tannenbaum's resulted from the research of highly-able youth, and Gagné's did not specify a population. The theorists differ, however, on the performance level required to be gifted/talented. The most liberal, Renzulli, considers the top 20% in creative-productive accomplishment whereas Tannenbaum considers only exemplary producers or performers as the desired outcome. Gagné falls within the middle of these two extremes with the top 10% included in the population. All agree that multiple components coalesce to bring about gifted performance.

In terms of elements necessary, the theorists may differ on the type of factors and the number of factors that combine to bring about demonstrated talent, ranging from three to five primary components. All claim that ability (domain-specific and/or general intellectual ability) is necessary. Each conceives that one's intrapersonal and environmental characteristics impact this process. Intrapersonal characteristics common to all include a form of motivation/commitment. Shared intrapersonal characteristics specified in two or more models are physical health/energy, mental health/energy, intensity of interest/passion, self-concept/self-awareness, creativity, values, autonomy, goal management, and learning/thinking approaches. Although Renzulli acknowledges the role of the environment, he fails to describe it. Tannenbaum and Gagné indicate the home, school, social, and cultural influences that comprise environmental aspects can impede or enhance talent. Tannenbaum and Gagné also describe the effect of chance. Only Gagné, however, specifies causal direction or ranks the causal contributions in talent development.

Relative to this research, weaknesses of these models include the absence of factors specific to adults that may potentially impact outstanding adult performance, including postsecondary education, career choice, adult family (i.e., spouse and descendants) and ongoing training to develop personally or occupationally. Because of the limited number of studies, research related to high-performing adults in math or numeracy was also examined.

Empirical Studies Related to Characteristics of High-Performing Adults in Numeracy/Math

Empirical research on the characteristics of U. S. adults who are highly skilled in numeracy is scant. Most of the data regarding highly-numerate individuals are from the ALL or PIAAC survey participants, which were previously described in the section *Numeracy Findings from Assessments* (beginning on page 20). It was, therefore, necessary to broaden the literature search. First, the examination of characteristics associated with high numeracy skill was expanded to include studies from the leading country of numeracy research, England. Second, studies relating to adults who demonstrated mathematical potential as youths or STEM talents as an adult are also described.

Numeracy in England/U.K.

England has researched and published more on the development of numeracy than any other English speaking country, starting with two national surveys in 1981 and dramatically increasing in the 1990s to include seven national surveys addressing numeracy (Carpentieri, Lister, & Frumkin, 2010). Reports on numeracy abilities, however, did not differentiate the very highest performers and, instead, typically focused on skills at the lower end of the spectrum. In fact, 25% of adults performed at the highest level (Level 2) on the 2003 Skills for Life survey of need (DfES, 2003). The highest level from the survey seemed fairly commonplace:

> Understands mathematical information used for different purposes and can independently select and compare relevant information from a variety of graphical, numerical and written material.
>
> - For example, calculating ratios and proportions, or determining median, mean and mode (Carpentieri, 2010, p. 12).

Intrapersonal characteristics associated with higher numeracy skills in general on the Skills for Life survey of need (DfES, 2003) included gender, age, race, language, and health (Carpentieri et al., 2010). For example, 33% of men performed at the highest level compared to 20% of women. Young adults and adults over 55, on average, performed more poorly than the remainder of the adults. Similarly, Rashid and Brooks (2010) reported a life-course trend in which adult numeracy skills typically increase through early middle age before plateauing and eventually declining. A greater percentage of White British individuals (27%) scored at the highest category (Level 2) compared to other races; 16% of Asian Indians scored at the highest levels. Respondents who spoke English as a second language did not perform as well. Individuals with higher numeracy were much less likely to report a disability and less likely to report poor health. On another survey that used items from Skills for Life, individuals with a very high risk for dyslexia were more likely to perform at the lowest numeracy levels (Bynner & Parsons, 2006).

Environmental characteristics associated with higher numeracy skills include maternal education, employment, and literacy skills. In general, higher parental education is associated with higher numeracy scores in adults. For example, individuals with mothers who did not pursue education after post-compulsory education was complete, were 1.5 times more likely to have poor numeracy skills (Carpentieri et al., 2010; Parsons & Bynner, 2007). Academically, individuals with higher numeracy levels were more likely to possess a degree and be employed full-time (Bynner & Parsons, 2006; Carpentieri et al., 2010). Numeracy skills can develop after adults have completed their terminal education especially if one’s occupation requires it (Carpentieri et al., 2010).

Conversely, numeracy skills declined when men and women were out of the workforce, and men with the lowest skills lost their skills sooner and declined the greatest (Bynner & Parsons, 1998). Numeracy and literacy skills on the Skills for Life survey were highly correlated; however, it should be noted that reading was required to complete numeracy tasks on the instrument. Over half (53%) earned a score that was one or more levels lower in numeracy compared to literacy. Furthermore, there was a relationship between numeracy skills and support given to their children as measured by the number of books participants provided their children; those who provided fewer books (less than 20) to their children were more likely to perform poorly on numeracy assessments (Bynner & Parsons, 1998).

Given a lack of data on individuals performing in the top 10% in numeracy, the research search was expanded to high-performing adults in math or STEM fields. Most of the empirical research related to high-performing or mathematically gifted adults in the last 50 years is sourced from individuals participating in national talent search programs, specifically the Study of Mathematically Precocious Youth which followed over 5,000 individuals from their identification of exceptional mathematical ability in youth to adulthood.

Gifted Education Studies Related to Mathematical Talent

Campbell and Feng (2010) used a sample of 190 U.S. Olympians in mathematics, physics, and chemistry from the 1970s to the 2000s to replicate Terman's (1954) study comparing the life success of 150 most successful men with the 150 least successful Termanites. Despite identical intellectual capabilities, Terman reported that fewer of the least successful men had a father who earned a college degree and fewer entered college or earned a bachelor's degree compared to the most successful. Furthermore, the most successful had almost 50% more books in their home. With respect to personality characteristics, the most successful group displayed intense curiosity and persistence. In contrast to Terman's identification based on a score on an IQ test, Campbell and Feng (2010) point out that Olympians must read and learn vast amounts of technical knowledge that goes far beyond what is taught in advanced high school courses which necessitate high levels of dedication. Using the rate of publications per year to divide the most successful from the least successful Olympians, the only significant differences between groups were that the more successful group were raised in a higher SES home and they had a more conducive home environment that included more books, stimulation, and encouragement to develop their talents.

Science Talent Search. The Science Talent Search, initally sponsored by the Westinghouse Corporation from 1942 to 1997 is a prestigious talent search science fair competition for high school students (Feist, 2006; Heilbronner, 2013). In the late 1990s, Intel Corporation became the sponsor but the Society for Science and the Public now sponsors it. Each year over 1,500 participants compete resulting in 300 semifinalists and 40 finalists. As an example of the potential for eminence, alumni include seven Nobel prize winners, 4 National Medal of Science awards, and 11 MacArthur Foundation Fellows (Heilbronner, 2013). Competitors select a research topic and identify an individual to mentor to help them conduct and analyze research.

Subotnik and Steiner (1994) reported on longitudinal research from Westinghouse Science Talent Search finalists. Of the original participants, 82% of the males and 66% of the females were still engaged in postsecondary studies or employment in mathematical or scientific domains at age 26.

In another article, Feist (2006) reported on two studies. One study followed individuals who demonstrated talent in youth, 161 Westinghouse Finalists from four cohorts (1965, 1975, 1985, 1995), and the second study reported on adults who were members of the National Academy of Sciences. Although the Westinghouse sample only included 31% women, the number of women per cohort increased from 25% in 1965 to 46% in 1995. Also decreasing over time, most participants were European-Americans (overall 83%, but decreasing to 66% in 1995), followed by Asian-Americans (15%) and Hispanic-Americans (3%). Additionally, 40% of participants had a father or mother who immigrated to the country or was first-generation. Although 70% of all Westinghouse science fair finalists earned a doctoral degree, 83% of the sample earned a doctoral degree including 11 from Harvard, 9 from MIT, 6 from Berkeley, 6 from Stanford, and 4 from Yale. Men and women were equally likely to obtain a doctoral degree, with no sex differences noted in the number of honors. Women, however, were more likely to leave the STEM field in college and in their career. Those who pursued science careers had children at younger ages than those who left the field.

With a goal of retrospectively examining early life predictors of eminence in STEM fields, Feist's (2006) second study included 112 members of the National Academy of Sciences. The vast majority were European-American (97%) or males (82%) with a mean age of 69 years old. Approximately one-third had an immigrant or first-generation mother or father. As expected, they had extremely high levels of productivity (publications and citations). Participants reported reasons for success included “scientific intuition,” “intelligence, and “drive persistence” (p. 30).

Helibronner (2013) also used two samples of finalists and semifinalists from the Science Talent Search (1987-1989 and 1997-1999) to investigate sex differences in educational and career representation in STEM fields. Reflective of national trends, the sample of females increased from 36% of the first cohort to 47% of the second cohort. Only 8% (6.8% males and 1.2% females) of the research projects were categorized as math-related, and 78.8% of research projects were from the science fields. On average, men participants scored significantly higher on the SAT-Mathematics than the women. Less than 1% of participants did not earn a bachelor’s degree, but approximately half earned a doctoral degree. Most (74.2%) selected a STEM major, but significantly fewer women selected a STEM major. Men also reported a higher STEM self-efficacy in college. A majority of participants (69%) were employed in a STEM field whereas 20% had never worked in the field. Women were more likely to study biology and men were more likely to major in physics or engineering. More women in the older cohort indicated leaving STEM fields because of a lack of compatibility with family responsibilities and desire for greater flexibility in work hours.

Study of Mathematically Precocious Youth (SMPY). Founded in 1971, SMPY’s primary purpose was to identify exceptional intellectual and mathematical talent at a young age (between 12-14) in order to facilitate individual talent development by providing specialized services tailored to their increased pace of learning (Lubinski, 2016; Lubinski & Benbow, 1994, 2006). To inform this aim, a 50-year study of talent was planned, tracking each cohort into adulthood at the following ages: 18, 23, 33, 50, and 65. Over 5,000 SMPY participants (5 cohorts) with mathematics and/or verbal talents were identified through talent search programs over a span of 25 years (1972-1997; see Table 2.2). Participants from the first three cohorts were selected on the basis of scores in the top 1% (*n* = 2,188), the top 0.5% (*n* = 778), or the top 0.01% (*n* = 501) of similarly-aged youth on either the verbal or math subtest of the SAT. Cohort 4 (*n* = 1,130) was comprised of adolescents who scored in the top 3% on any subtest of a grade-level standardized achievement test. Selected to investigate the fidelity of the SMPY talent search model in STEM fields, Cohort 5 (*n* = 714) included graduate students who were enrolled at one of the 15 top-ranked math, engineering, or science graduate programs (Lubinski & Benbow, 2006). The following sections describe findings from the longitudinal research related to intrapersonal and environmental characteristics of these highly-able adults.

Environmental characteristics. Parent educational attainment and parent immigration status were associated with SMPY identification. Many participants had at least one parent who immigrated to the United States (Lubinski et al., 2006). Over 20% of SMPY graduate school participants had at least one foreign-born parent and 31% of talent search participants had a foreign-born parent, and the percentages were even greater for the most successful participants. Benbow and Arjmand (1990) found that the most powerful family variables in discriminating between high postsecondary academic achievers and low achievers were paternal educational level and encouragement to attend college.

Table 2.2

Description of SMPY Cohorts 1 to 5

Cohort	Years Selected	Age of Selection	Selection Criteria	Ability Represents top	Sample primarily from	*n*
1	1972-1974	12-13	Minimum score: 390 SAT-M or 370 SAT-V	1%	Maryland	2,188
2	1976-1979	12	Minimum score: 500 SAT-M or 430 SAT-V	0.5%	mid-Atlantic states	778
3	1980-1983	12	Minimum score: 700 SAT-M or 630 SAT-V	0.01%	national representation	501
4	1992-1997	12-14	Top 3% of any subtest on a grade-level standardized achievement test	3%	Mid-West states	1130
5	1992	23-25	1st and 2nd-year graduate students enrolled in a top 15 U.S. STEM graduate program			714

Retrospectively, almost 70% of participants indicated that they perceived educational acceleration as beneficial for their education and approximately 40% felt that it positively contributed to their career development (Benbow et al., 2000). Furthermore, 80% of participants were *very* or *somewhat* unsupportive of eliminating ability grouping with other high potential students (i.e., homogeneous ability grouping). Additional research with both the SMPY participants identified through the adolescent talent search and those identified as graduate students found a relationship between enriched STEM exposure with STEM educational attainment and STEM occupational achievement(Wai, Lubinski, Benbow, & Steiger, 2010). In other words, those who had higher exposure to precollege educational experiences (e.g, Advanced Placement courses, science fair/math competitions, college courses in high school, inventions, special classes, or research in STEM areas) were associated with greater levels of PhDs, tenure, publications, and employment in the STEM field.

Educational outcomes of SMPY participants have been reported. By their 50s, approximately one-third of former SMPY participants (top 1%) earned their master's degree and 25%-40% earned their doctorate (Lubinski & Benbow, 2006; see Table 2.3). Of the most-able participants (top 0.01%), over 50% earned doctoral-level degrees (e.g., PhD, MD, JD; Lubinski, Benbow, Webb, & Bleske-Rechek, 2006) compared to today's average of 1.9% of US adults over the age of 25 (US Census Bureau, 2017). Many participants (48% of Cohort 1; 64% of Cohort 2) eventually earned at least one postsecondary degree in math or science (Benbow et al., 2000). Sex differences were observed as females were or likely to earn a degree in biology, medicine or humanities, and males were more likely to earn degrees in engineering or inorganic sciences. The largest number of terminal bachelor's degrees was in engineering (31% males and 13% females). Given that the previous studies included only the most precocious youth (at or above the 99th percentile), these percentages may overestimate postsecondary completion as Wai (2014) found that the percentage of participants earning postsecondary and graduate degrees increased as ability increased.

Table 2.3

Education Outcomes at 40-Year Follow-up (Lubinski et al., 2014)

	Bachelor	Master's	Doctorate	Total
Cohort 1 - Males	27%	30%	33%	90%
Cohort 1 - Females	32%	35%	25%	92%
Cohort 2 - Males	25%	32%	40%	97%
Cohort 2 - Females	29%	32%	38%	99%

There were sex differences related to occupational categories and earned income (Benbow et al., 2000; Lubinski et al., 2014). At the 20-year follow-up, the majority (69.3%) of the participants identified as high-potential youth were postsecondary teachers, engineers, or scientists compared to Cohort 5 (45.8%) who identified as graduate students (Lubinski et al., 2006). By midlife, the most frequently reported occupational categories for men were chief executives, information technology, STEM fields, postsecondary faculty, business directors/managers/owners, and lawyers/judges (Lubinski et al., 2014). The most frequently reported for women were health science, chief executives, information technology, STEM fields, postsecondary faculty, PK-12 teachers, and full-time homemaker (Lubinski et al., 2014). These figures include the 1.8% tenured at a top-to institution of higher education and 4.1% tenured at a research university. Another 2% were employed as a top executive at a Fortune 500 or other "name brand" organization. Men and women were equally represented in finance, law, and medicine. The median midlife income for males was higher than females ($138,000-$140,000 vs. $78,000-$80,000), but more men (89%-90%) worked full time compared to females (59%-69%). If only full-time employment was considered, differences between genders were less still significant ($142,000-$150,000 for males vs. $100,000 to $101,000 for females). Despite sex differences in occupations and income, SMPY participants reported, on average, uniformly high satisfaction with their professional career success, the current direction of their professional career. These reports were consistent across the lifespan (Ferriman, Lubinski, & Benbow, 2009; Lubinski et al., 2006; Lubinski et al., 2014).

Intrapersonal characteristics. Follow-up studies have provided information on SMPY participants related to intrapersonal characteristics. Demographic information includes race/ethnicity, gender, and reports about family relationships and the number of children. Other intrapersonal items reported below relate to differences in ability pattern and motivation/task commitment.

With respect to ethnicity, the vast majority of participants from Cohorts 1 to 4 were Caucasian (96.1%, 89.2%, 76.8%, and 87.5% respectively) followed by Asian (2.0%, 5.9%, 19.4%, and 10.2%, respectively) (Achter, Lubinski, & Benbow, 1996). Cohort 5 (selected as adults) was comprised of 85% Caucasian, 9% Asian, 2% African American, and 2% Black (Ferriman, 2008).

Except for Cohort 5, which was intentionally selected to equalize men and women participants (Ferriman et al., 2009; Lubinski et al., 2001), the cohorts were largely comprised of males. In the initial SMPY sample, there were 80% more males than females (Webb, Lubinski, & Benbow, 2002). It is likely that the disproportionate representation of males increased as selectivity increased. For example, the ratio of male to female adolescents scoring at least 500 on SAT-M was 2:1, scoring at least 600 was 4:1, and scoring at least 700 was approximately 12:1 (Benbow, 1988; Benbow et al., 2000). Furthermore, when Webb et al. (2002) narrowed the sample to those with math-science aspirations, the ratio of males to females was 2.2 to 1.0. Of the total participants who responded to the 20-year and 40-year follow-up research, 32% to 39% were females (Benbow et al. 2000; Lubinski et al., 2014).

Most participants (72% to 82%) were married or in a long-term relationship (Benbow et al., 2000; Lubinski et al., 2014). In their mid-30s, over 60% of participants did not have children (Lubinski et al., 2006), but by midlife (40-year follow up), the percentage of individuals with children increased. The researchers noted that the reproductive rates were markedly lower than their non-SMPY similarly-aged peers but were closer to peer women with graduate degrees (Lubinski et al., 2006). By midlife, only one-quarter of SMPY participants reported having no biological children (Lubinski et al., 2014). Of those participants with children, the mean number of children ranged from 1.96 to 2.21, depending on the gender and cohort.

SMPY researchers found that the strength patterns of verbal, spatial, and math patterns in adolescence predicted the educational and vocational domains chosen as adults (Lubinski & Benbow, 2006; Lubinski et al., 2001; Lubinski, Webb, Morelock, & Benbow, 2001; Park, Lubinski, & Benbow, 2007; Robertson, Smeets, Lubinski, & Benbow, 2010; Webb et al., 2002). Participants tended to choose professions that complemented their areas of greatest strength (Lubinski, 2016). For example, graduate students in the math and the natural sciences (i.e., quantitative tilt) scored significantly higher on SAT-M compared to SAT-V (Lubinski et al., 2001). Although participants were all strong in mathematics, those who possessed greater verbal strengths (i.e., qualitative tilt) were more likely to earn a humanities degree or law degree whereas those with relative strengths quantitatively were more likely to earn a STEM degree (Park et al., 2007). Similarly, those with qualitative tilts were also associated with literary publications such as novels or nonfiction and those with quantitative tilts were associated with patents. Although both sexes of SMPY participants were mathematically talented, the women tended to have even greater verbal strengths (Lubinski et al., 2001; Webb et al., 2002) and, therefore, were more likely to pursue occupations that complemented their verbal strengths.

Participants were queried about their views on talent development and perceived that developing talent was beneficial for personal success (Benbow et al., 2000). On average, participants indicated that they agreed with the statement, “It takes a lot of hard work to develop talent/skills” (Benbow et al., 2000, p. 478). Furthermore, they tended to disagree that talent outweighed hard work when it pertained to achieving success. Statistically, there were no differences between male and female responses.

Throughout their lifespan, however, females were less willing to work as many hours at their job and were more likely to work part-time or be a homemaker (Ferriman et al., 2009; Lubinski et al., 2006; Lubinski et al.,2014,; Robertson et al., 2010). On average, men reported investing 11 hours per week more than women in their work and career development whereas women devoted significantly more time to home and family than the men (Lubinski et al., 2014). As a way to measure time devoted to developing expertise, participants were queried about the amount of time an individual would be willing to invest in an ideal job, 30% of women and 7% of men were unwilling to invest more than 40 hours. Women, however, on average preferred to work fewer hours in their career in order to achieve more balance in their life (Robertson et al., 2010). This differential becomes first noticeable when participants were in their mid-30s as women who became mothers were more likely to reorient their priorities to working fewer hours, flexibility, and freedom from work demands on the weekends (Ferriman et al., 2009).

Rationale for the Study

Given an increasing dependence on science and technology, numerical understanding has become increasingly important (Steen, 2002). The success of individuals and economies are linked to individuals' numerate abilities (PIAAC Numeracy Expert Group, 2009). Numeracy skills are associated with employment levels because they are essential for businesses that need quantitatively literate individuals. Numeracy is also essential for success in STEM-related postsecondary fields. Furthermore, from an ethical or egalitarian standpoint, some argue that mathematical understanding and education is the "biggest barrier to upward mobility in educational attainment" and "quantitative literacy is about democratization of mathematics" (Steen, 2002, p. 1).

A gap in the literature pertaining to the characteristics of adults performing at the highest level of numeracy exists. A comprehensive summary of individuals performing at the highest levels of numeracy could not be found. Instead, researchers are prone to examine adults performing at the lowest levels of numeracy. The research examining gifted adults is not sufficient for multiple reasons: most adult participants are selected based on their (a) performance as a youth (e.g., Science Talent Search, SMPY, etc.) and not on adult achievement; (b) mathematical abilities (which differ from numeracy that are more focused on the application of quantitative concepts in everyday activities); and (c) their potential at the extremely high levels (i.e., the top .01% to 1%).

Weaknesses in the numeracy and talent development models have also been highlighted. Numeracy models focus on K-12 education and do not indicate characteristics associated with outstanding performers. Talent development models have not been empirically tested and do not specifically include adult contexts/relationships such as employment, higher education, and other training/education outside of the workplace. This study will, therefore, contribute to the field by examining the relationships between intrapersonal and environmental variables and characteristics of outstanding adult performers in numeracy.

CHAPTER THREE

Method

This chapter describes the research questions, sample participants, data collection process and instruments, and the variables that were used in the SEM analysis. After outlining the participants and data collection, data analysis procedures are described. Finally, methods for examining the data, preparing descriptive statistics, and conducting the Confirmatory Factor Analysis (CFA) and SEM procedures are outlined.

The purpose of this present study is to examine the relationships between numeracy proficiency, environmental and intrapersonal characteristics of the highest performing U.S. adults on numeracy proficiency. Data from a large-scale, nationally representative survey, the Program for the International Assessment of Adult Competencies (PIAAC) was used. Specifically, three primary research questions were addressed. The first two questions were answered with descriptive statistics for both groups (below the 90th percentile and top 10%). The third question will use Structural Equation Modeling (SEM) to examine the effects of environmental and intrapersonal characteristics on numeracy proficiency as shown in the conceptual model in Figure 3.1.

1.0 What are the characteristics of U.S. adults who perform in the top 10% in numeracy proficiency?

    1.1 What are the environmental characteristics of U.S. adults who perform in the top 10% in numeracy proficiency?

    1.2 What are the intrapersonal characteristics of U.S. adults who perform in the top 10% in numeracy proficiency?

2.0 What are the characteristics of U.S. adults who perform below the 90th percentile in numeracy proficiency?

2.1 What are the environmental characteristics of U.S. adults who perform below the 90th percentile in numeracy proficiency?

2.2 What are the intrapersonal characteristics of U.S. adults who perform below the 90th percentile in numeracy proficiency?

3.0 To what extent do environmental characteristics and intrapersonal characteristics predict differences in numeracy proficiency for U. S. adults?

Participants

Sampling

Developed by the Organization for Economic Cooperation and Development (OECD), to date a total of 250,000 adults were surveyed in the official language of their country in 2012 (24 countries), 2014 (9 other countries), and 2017 (5 additional countries) (NCES, 2018.; OECD, 2018). The U.S. received approval from the PIAAC Consortium for its sample design and selection plan which ensured compliance with the PIAAC Consortium's *Technical Standards and Guidelines* (Hogan et al., 2016; OECD, 2014). The necessary sample size was determined by the number of languages for administration and the number of cognitive domains assessed (OECD, 2016b). Given that the U.S. assessed all three competency domains, the minimum required sample size was 5,000. Second, per OECD's (2016b) stipulation that countries may choose to oversample certain subgroups of the population to obtain more precise estimates, the U.S. conducted the 2014 National Supplement. The PIAAC household sample included 8,670 participants collected from two administrations: the 2012 Main Study and the 2014

National Supplement. Participants in either administration were paid $50 for responding to the questionnaire upon completion (Hogan et al., 2016).

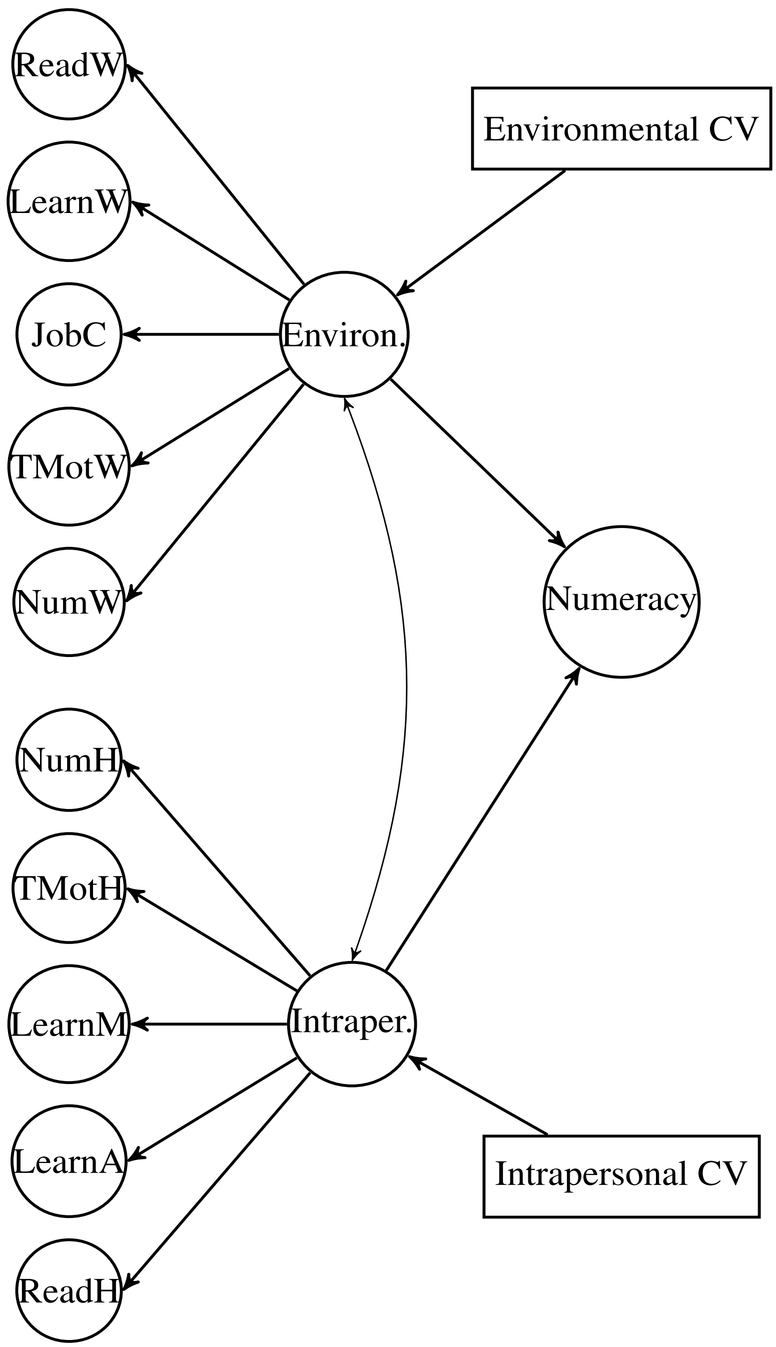

Figure 3.1. Adult Numeracy Achievement conceptual model. A model of effects of intrapersonal and environmental characteristics associated with numeracy achievement. Environmental and intrapersonal covariates have been drawn as one box to simplify the model.

Main Study. The 2012 U.S. Main Study identified sample households based on a nationally representative 4-stage, stratified area probability sampling frame that began at the county level. At the first stage, 80 primary county sampling units were selected, and at the second stage, 901 block groups were identified (Hogan et al., 2016). Third, 9,648 housing units housing units were chosen, but after removing households that were unoccupied, were no longer a housing unit, or did not contain an adult between the ages of 16 to 65, 6,916 households remained (Goodman et al., 2013). At the fourth stage, 6,100 adults were selected based on eligibility criteria but, of those, only 5,100 completed the background questionnaire (n = 4,898) or had background data (n = 112) added because of a literacy-related barrier (Goodman et al., 2013).

National Supplement. With a goal of learning more about young adults, unemployed adults, and older adults, the second wave of data was collected. Accordingly, the 2014 National Supplement sampled noninstitutionalized adults from each of the following categories: unemployed adults (age 16-65), young adults (age 16-34), and older adults (age 66-74) (Hogan et al., 2016). Accordingly, adults (age 35-65) who were identified as not in the labor force or were employed in the screening interview were excluded in the screening stage. For the National Supplement, a two-frame sample approach was chosen for its efficiency in sampling atypical populations. The first sample frame was conducted in a similar manner to the 2012 collection. Area samples were selected from the same 80 primary county sampling units used and block groups used in the Main Study. Next, 9,579 identified households resulted in 3,617 individuals. Of those, 2,790 participated in the sample. The second sample frame began with the same 80 primary county sampling units. Within each of the county units, five high-unemployment tracts were identified and, of those, one county unit was randomly selected. Households (n = 6,956) were selected from a U.S. Postal Service address list. After screening out employed adults, 870 individuals completed the survey. Given sampling procedures for the National Supplement, the data collected in this wave is not meant to stand alone but to increase the precision of subgroup estimates.

This Research Sample

To investigate the research questions of this study, the PIAAC 2012/2014 U.S. National Supplement Public Household Data File (prgushp1_puf) was downloaded from the NCES website at https://nces.ed.gov/surveys/piaac/datafiles.asp. After eliminating all participants that were under 16 or over 65 (n = 753) and those who had not been employed in the past 12 months, (n = 1, 302), 5,862 adult participants remained in the data set.

Data Collection

Instruments

Three instruments were used to collect data from sampled individuals. The purpose of the Screener was to identify individuals eligible to participate in the study. The Background Questionnaire was administered to individuals who were selected from the screening process. Following completion of the Background Questionnaire, participants took the Direct Assessment. Participants took, on average, about two hours to complete the interview and competency assessment.

Screener. Interviewers used a computer-assisted personal interviewing (CAPI) instrument to collect the first name, gender, and age of all members within households selected by the nationally representative probability sampling process to determine potential eligibility for the PIAAC survey (Hogan et al., 2016). Up to two persons per household who were between the age of 16 and 65 were qualified for selection for the Main Study. Questions regarding employment status were added to the screener for the 2014 National Supplement data collection process. After the collection of screener data, the CAPI system selected sample persons. As part of the screening, race/ethnicity and a phone number to verify work status were collected from participants.

Background questionnaire. Participants' background information was collected via a face-to-face interview using computer-assisted personal interviewing (CAPI) software provided by the PIAAC Consortium (Goodman et al., 2013). As preprogrammed skip patterns and follow-up probes were determined based on participant responses to individual items, not all individuals received every background question. The Background Questionnaire was comprised of 10 sections designed to collect demographic, education, employment, and use of skills at work and in everyday life (see Table 3.1). The PIAAC Background Questionnaire may be accessed at http://www.oecd.org/skills/piaac/samplequestionsandquestionnaire.htm.

Direct assessment. Although participants typically completed the Direct Assessment on a computer, individuals with limited computer familiarity were provided with a paper-based version if they were unwilling to complete the assessment on the computer or if they did not pass the computer-based Core Stage 1 or Stage 2 (approximately 14%; OECD, 2016b). To pass Core Stage 1, respondents must demonstrate the ability to use the computer to highlight text as well as complete at least three of the following tasks: clicking, scrolling, typing, dragging and dropping text, or selecting from a pull-down menu (Hogan et al., 2016). Upon successful completion of Core Stage 1 tasks, participants continued to computer-based Core Stage 2, which provided six tasks to measure basic literacy and numeracy skill (Goodman et al., 2013; Rampey et al., 2016). Successful completion of Core Stage 2 was followed by the computer-based Direct Assessment. (Respondents (0.8%) lacking the basic literacy and numeracy skills for the Direct Assessment, were provided a reading components test.)

Immediately following the Core Stage 2, respondents were randomly assigned to complete either a numeracy, a literacy, or a problem-solving assessment (Rampey et al, 2016). After completion of the first module, the respondents were presented with a second randomly-assigned module. As only two of the three domains were presented to any computer-based test taker, not all PIAAC participants completed the numeracy assessment. Only 66% of respondents who successfully completed the Core Stage 2 were presented a numeracy module. Furthermore, the computer-based competency assessments were adaptive, meaning that participants are presented with different questions based on their performance to the first set of items. In other words, each module taken on the computer contained adaptive “testlets” that corresponded to varying difficulty levels in numeracy and literacy based on participants’ performance (Goodman et al., 2013; Rampey et al., 2016). Accordingly, respondents do not see the same items. The complex sampling design and adaptive testing must be taken into account when analyzing data (Rampey et al., 2016).

Table 3.1

Background Questionnaire Categories (Hogan et al., 2016)

Variable Prefix	General Category	Who Responds	Items about
A	General Info	All	gender, year of birth;
B	Education & Training	All	formal education history, formal and informal educational activities in the past year;
C	Work History	All	work status at the time of the interview, work history;
D	Current Work	Currently employed or self-employed	current earnings, hours worked, employment title, responsibilities, industry, economic sector, length of employment, size of employer, supervision/ management responsibilities, flexibility of work, occupational requirements,
E	Last Job[1]	Not currently employed but worked in <5 years	job title, responsibilities, industry, economic sector, length of employment, size of employer, supervision/management responsibilities, hours worked, reason job ended;
F	Generic Skill Use at Work	If employed in past year	frequency of use of generic skills at work such as communicating, planning, presenting, influencing, problem-solving skills;
G	Specific Skill Use at Work	If employed in past year	frequency of use of skill usage at work related to numeracy, literacy, or problem-solving with technology;
H	Specific Skill Use in Everyday Life	All	frequency of use of skill usage in everyday life related to numeracy, literacy, or problem-solving with technology;
I	About Yourself	All	learning strategies, cultural engagement, political efficacy, social trust, learning disability, health status and methods gathering information about health issues;
J	Background Information	All	household size, number and age of children, partner's employment status, country of birth, immigration status, ethnicity, languages spoken, parents' immigration and education background

Note. [1]Last job section was only for those who were not working at the time of the survey but had work experience.

The PIAAC was the first international survey to use multi-stage adaptive testing, which used "adaptive algorithms to optimize the delivery of test items within a domain to estimated proficiency levels of individuals" (Kirsch & Thorn, p. Foreward-6). There are multiple advantages to this testing design: (a) information can be gathered in less time; (b) compared to individual items, adaptive clusters decrease the likelihood of item-by-country interactions; (c) it is equally informative for all proficiency ranges, from the lowest to the highest; and compared to single question computer adaptive tests, (d) the multistage adaptive design is more accurate because algorithms select the subsequent cluster based on responses to one or more items and (e) items can go beyond the typical multiple-choice design because the computer has more time to score the response while the individual completes the cluster of items in a testlet (Kirsch & Thorn, 2016). Sample questions may be found at http://www.oecd.org/skills/piaac/samplequestionsand questionnaire.htm.

Variables

Variables selected for inclusion were based on the literature review and talent development theoretical models as previously described. The primary variable of interest for the selection of participants was numeracy proficiency. Other than the proficiency scores, other variables were selected from the background survey to align with the research literature and theoretical models related to gifted adults with talents - environmental and intrapersonal variables. Although some other specific PIAAC items may have provided information of interest, questions that were not presented to practically the entire sample were omitted.

The survey also included six PIAAC-designed scales as factors (e.g., Numeracy at home, Numeracy at work, Reading at home, Reading at work, Learning at Work, Readiness to Learn) as well as some selected items drawn from other PIAAC-constructed scales. Scale items queried frequency or extent of behavior using an ordinal scale. The frequency level response options were *never, less than once a month, less than once a week but at least once a month, at least once a week but not every day,* or *every day*. Scales that measure the extent, such as learning approach questions, used the following response options: *not at all, very little, to some extent, to a high extent,* or *to a very high extent*.

Endogenous/Outcome Variable- Numeracy Proficiency

An endogenous variable is an outcome or dependent variable (Kline, 2016). As shown in Figure 3.1, the outcome variable is numeracy proficiency, which ranges from 0 to 500. PIAAC reports indicate five proficiency levels for numeracy (see Table 3.2): Below Level 1 (0-175), Level 1 (176-225), Level 2 (226-275), Level 3 (276-325), Level 4 (326-375) and Level 5 (score 376-500). Per OECD (2013a) conventions, however, Level 4 and Level 5 have been combined in all reports as less than 2% of adults internationally performed at level 5 in numeracy (Rampey et al., 2016). For purposes of this study, the outcome variable, numeracy proficiency, was dichotomized to represent the bottom 90% (value = 0) and the top 10% (Levels 4/5; value = 1).

As PIAAC is an adaptive assessment, however, participants did not see every numeracy item, and therefore individuals are not provided a single “true” score to describe their numeracy proficiency. Rather, each respondent has a set of 10 plausible values for numeracy (PVNUM1 – PVNUM 10) randomly selected from their estimated

Table 3.2

PIAAC Proficiency Levels in Numeracy[1]

Level & cut scores	Tasks at this level require the respondent to understand…	% U.S. Adults	% Intl. Adults
Level 5 (376-500)	complex representations, abstract, formal mathematical, and statistical ideas, possibly embedded in complex texts. Respondents may have to integrate multiple types of mathematical information where considerable translation or interpretation is required; draw inferences; develop or work with mathematical arguments or models; and justify, evaluate and critically reflect upon solutions or choices.	1%	2%
Level 4 (326-375)	a broad range of mathematical information that may be complex, abstract or embedded in unfamiliar contexts. These tasks involve undertaking multiple steps and choosing relevant problem-solving strategies and processes. Tasks tend to require analysis and more complex reasoning about quantities and data; statistics & chance; spatial relationships; change, proportions and formulas. Tasks at this level may also require understanding arguments or communicating well-reasoned explanations for answers or choices.	9%	10%
Level 3 (276-325)	mathematical information that may be less explicit, embedded in contexts that are not always familiar and represented in more complex ways. Tasks require several steps and may involve the choice of problem-solving strategies and relevant processes. Tasks tend to require the application of number & spatial sense; recognizing & working with mathematical relationships, patterns, & proportions expressed in verbal or numerical form; interpretation and basic analysis of data and statistics in texts, tables and graphs.	29%	35%
Level 2 (226-275)	to identify and act on mathematical information and ideas embedded in a range of common contexts where the mathematical content is fairly explicit or visual with relatively few distractors. Tasks tend to require the application of two or more steps or processes involving calculation with whole numbers and decimals, percents and fractions; simple measurement and spatial representation; estimation; and interpretation of relatively simple data and statistics in texts, tables and graphs.	34%	34%
Level 1 (176-225)	to carry out basic mathematical processes in common, concrete contexts where the mathematical content is explicit with little text and minimal distractors. Tasks usually require one-step or simple processes involving counting, sorting, performing basic arithmetic operations, understanding simple percents such as 50%, and locating and identifying elements of simple or common graphical or spatial representations.	19%	14%
Below Level 1 (0-175)	to carry out simple processes such as counting, sorting, performing basic arithmetic operations with whole numbers or money, or recognizing common spatial representations in concrete, familiar contexts with explicit math content with little or no text or distractors.	8%	5%

Note. [1]Adapted from Rampey et al. (2016).

probable proficiency distribution on a scale from 0 to 500. By using multiple imputations of proficiency values derived from test item scores and background information, these plausible values reflect individual performance combined with the performance of similar respondents and result in more accurate estimates of population parameters (Hogan et al., 2016; Yamamoto, Khorramdel, & von Davier, 2016). The manner for dealing with plausible scores is detailed in the data analysis section.

Environmental Variables

Variables selected to report demographic information descriptively or to represent environmental characteristics are described in the following section. Table 3.3 displays the single environmental variables and Table 3.4 displays the cluster of items used to form factors (i.e., unobservable environmental constructs).

Family of origin and cultural capital. Covariates were selected to measure the characteristics of participants' family of origin. The highest level of education obtained by the respondent's mother (J_Q06BUS) and father (J_Q07BUS) provided the following response options: less than high school diploma (code = 1), high school diploma/some college (code = 2), or associate's college degree or higher (code = 3). Whether the respondent's mother/female guardian (J_Q06A) and father/male guardian were born in country were covariates, The number of books in participant's home at age 16 (J_Q08) was used to indicate cultural capital with these response options: 10 books or less (code = 1), 11 to 25 books (code =2), 26 to 100 books (code = 3), 101 to 200 books (code = 4), 201 to 500 books (code = 5), more than 500 books (code = 6).

Long-term relationships and children. As long-term relationships and whether an individual has children are not theorized to impact talent development, per se, these variables were reported descriptively only and were not be included in the models. Information on if the respondent is living with their spouse or partner (J_Q02A) and the work situation of that partner (J_Q02C) was provided as a descriptive but was not included in the model. Whether respondents had children (J_Q03A) was also provided as a descriptive only.

Table 3.3

PIAAC Items Used as Environmental Covariates

Measures	Item Code and Description
Mother-Education	*J_Q06BUS* Background - Mother/female guardian - Highest level of education
Mother -Native	*J_Q06A*[1] Background - Mother/female guardian – Whether born in country
Father-Education	*J_Q07BUS* Background - Father/male guardian - Highest level of education
Father-Native	*J_Q07A*[1] Background - Father/male guardian – Whether born in country
Cultural Capital	*J_Q08* About how many books are/were there in your home when you were 16 years old
Education	*EDCAT6* Highest level of formal education
Employment	*C_D05* Employment status derived (employed, unemployed, out of workforce)
Income	*D_Q18AT* Annual net income by quintile (derived)

Note. [1]Items coded with a yes = 1 and no = 2.

Education. Two variables were selected to measure education: highest level of formal education earned (EDCAT6) and area of study (B_Q01B). The variable EDCAT6 divided terminal education into six levels: *Lower secondary or less* (ISCED 1,2, 3C short or less); *Upper secondary* (ISCED 3A-B, C long); *Post-secondary, non-tertiary* (ISCED

4A-B-C); *Tertiary - professional degree* (ISCED 5B); *Tertiary - bachelor degree* (ISCED 5A); and *Tertiary - master/research degree* (ISCED 5A/6).

Employment. The employment variable (C_D05) indicated if the respondent's occupational status: employed (code = 1), unemployed (code = 2), or out of the labor force (code = 3). Social class was measured using the trend variable, annual income by quintile (D_Q18AT), in which ordinal values ranged from 0 (no income) to 5 (highest quintile – i.e., top 20%).

Factors. Numeracy at Work, Reading at Work, Technical/Computer Skills at Work, Learning at Work, and the Job Culture were chosen as environmental factors (see Table 3.4). Numeracy at Work was a PIAAC-designed scale comprised of six items (G_Q03B, C, D, F, G, H) with Cronbach's Alpha at .85 (SD = 0.02) across all countries, however it was noted that the average item-test correlation close to .3 (M = .29, SD =0.06) (Allen et al., 2016). As numeracy and literacy are highly correlated (Kirsch, Yamamoto, & Garber, 2016), investing in work-related literacy skills is expected to contribute to numeracy proficiency as well. Reading at Work is another PIAAC-designed scale comprised of eight items (G_Q01A-H) with Cronbach's Alpha at .82 (SD = 0.04). Learning at Work included three items PIAAC intended to measure investment in training (D_Q13A-C). Another factor, Technical Skills at Work, included four selected items (G_Q05C, D, E, G) from the PIAAC-designed Information and Communication Technology (ICT) at work subscale intended to represent technical/computer skills used at work. While we only selected four of the items PIAAC's entire ICT scale of 8 items had a Cronbach's Alpha at .82 (SD = 0.04) and the average item-test correlation was

Table 3.4

PIAAC Items Comprising Environmental Factors

Factor	Item Code and Description
	In your job, how often do/did you usually…
Numeracy at Work	*G_Q03B* calculate prices, costs or budgets?
	G_Q03C use or calculate fractions, decimals or percentages?
	G_Q03D use a calculator - either hand-held or computer based?
	G_Q03F prepare charts, graphs or tables?
	G_Q03G use simple algebra or formulas?
	G_Q03H use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques?
Reading at Work	*G_Q01A* read directions or instructions?
	G_Q01B read letters, memos, or email?
	G_Q01C read newspapers or magazines?
	G_Q01D read articles in professional journals or scholarly publications?
	G_Q01E read books, fiction or non-fiction?
	G_Q01F manuals or reference materials?
	G_Q01G read financial statements?
	G_Q01H read diagrams, maps, or schematics?
Technical Motivation at Work	*G_Q05C* use the internet to collect work-related information?
	G_Q05D use the internet to conduct work-related transactions?
	G_Q05E use spreadsheets?
	G_Q05G use a programming language to program/write computer code?
	How often does your job usually involve…
Learning at Work	*D_Q13A* learning new work-related things from co-workers or supervisors?
	D_Q13B learning-by-doing from the tasks you perform?
	D_Q13C keeping up to date with new products or services?
	How often does your current/last job usually involve…
Job Culture/ Problem-Solving	*F_Q03A* planning your own activities?
	F_Q03B planning the activities of others?
	F_Q03C organizing your own time?
	F_Q05A Think of "problem solving" as what happens when you are faced with a new or difficult situation which requires you to think for a while about what to do next. How often are/were you usually faced by relatively simple problems that took no more than 5 minutes to find a good solution?
	F_Q05B How often are/were you usually confronted with more complex problems that took at least 30 minutes to find a good solution?

smaller than .3 (*M* = .23, *SD* =0.10) (Allen et al., 2016). The final factor attempted to measure job culture/problem-solving using five items (F_Q03A, B, C; F_Q05A-B). All of the items comprising environmental factors were measured using the following frequency categories: 1 (*never*), 2 (*less than once a month*), 3 (*less than once a week but at least once a month*), 4 (*at least once a week but not every day*), and 5 (*every day*).

Intrapersonal Variables

Intrapersonal variables included items specific to the individual such as gender, race/ethnicity, age, and whether the respondent was a native speaker. Gender (GENDER_R) was coded 1 for male and 2 for female. The race/ethnicity (RACETHN4CAT) variable was recoded using dummy coding using White as the reference category (code = 0). Age (AGEG10LFS) was measured in 10-year bands using the following codes: 1 (age 24 or less), 2 (25-34), 3 (35-44), 4 (45-54), and 5 (55-65). Whether the PIAAC assessment was provided in the native language of the respondent (NATIVELANG) was coded 1 if it was given in native language or 0 if it was not given in the respondent's native language. Persistence (B_Q03A) asked if the respondent ever began studying for a degree but discontinued prior to completion (yes = 1, no = 2). Table 3.5 displays the intrapersonal covariates and Table 3.6 displays the cluster of items comprising the intrapersonal factors.

Health and disability. Personal variables for inclusion related to perceived health and disability status. A self-rating of health (I_Q08) was a covariate with categories ranging from 1 (*excellent*) to 5 (*poor*). The presence of a learning disability

(I_Q08USX3) and difficulty seeing print (Q08USX1) were the two disability status covariates (yes = 1, no = 2).

Table 3.5

PIAAC Single Items used as Intrapersonal Covariates

Covariate	Item Code and Description
Gender	*GENDER_R*
Race	*RACETHN_4CAT* Race/ethnicity (4 categories)
Age	*AGEG10LFS* Age groups in 10-year bands
Native Lang.	*NATIVELANG* Test is in native language
Health	*I_Q08* In general, would you say your health is excellent, very good, good, fair, or poor?
Learning Disability	*I_Q08USX3* Have you ever been diagnosed or identified as having a learning disability?
Vision Problems	*I_Q08USX1* Do you have any difficulty seeing the words and letters in ordinary newspaper print even when wearing glasses or contact lenses, if you usually wear them?
Persistence	*B_Q03A* Did you ever start studying for any formal degree but leave before completing it?

Factors. The factors used to measure intrapersonal characteristics are reported in Table 3.6. Seemingly, items measuring the investment in numeracy outside of employment responsibilities indicate a commitment to developing these skills. Accordingly, two environmental factors measuring numeracy use and technical skill use at work have parallel items measuring skill use outside of work which were included as intrapersonal factors. The factor, Numeracy at Home, was a PIAAC-designed scale to measure numeracy proficiency in everyday life (H_Q03B-D & F-H) and had a Cronbach's Alpha of .84 (*SD* = 0.02) (Allen et al., 2016). Technical/Computer Skill Use at Home included four selected items (H_Q05C, D, E, & G) from the PIAAC-designed use of ICT at home scale. The original ICT scale of 8 items had a Cronbach's Alpha at

.76 (*SD* = 0.03) and the average item-test correlation was smaller than .3 (*M* = .23, *SD* =0.10) (Allen et al., 2016).

Task commitment was also measured by personal application to continued learning, or Learning Motivation. Items for this factor asked respondents about their participation in learning opportunities outside of a formal educational program such as distance education, on-the-job training, seminars, workshops, or private lessons, (B_Q12A, A_T, C, E, G, and B_Q02A _T1). These items were all measured using a categorical variable (yes = 1, no = 2).

Three PIAAC-designed subscales were used as approaches to learning factors. The first, Learning Approach, was designed to measure deep learning; it was comprised of 5 items (I_Q04B-M) and had a Cronbach's Alpha of .78 (Allen et al., 2016). A Likert-type scale was also used for the items comprising the Learning Approach factor ranging from 1 (*not at all*), 2 (*very little*), 3 (*to some extent*), 4 (*to a high extent*), and 5 (*to a very high extent*).

Given that numeracy and literacy are highly correlated (Kirsch et al., 2016), improving literacy skills at home is an investment in everyday life that is hypothesized to contribute to numeracy proficiency indirectly. Reading at Home was comprised of eight items (H_Q01A-H). These items had a .72 Cronbach Alpha (*SD* = .06) across participating countries, but the average item-test correlation was less than .3 (*M* = .28, *SD* = .07) (Allen et al., 2016).

The items comprising the factors Numeracy at Home, Technical Motivation at Home, and Reading at Home were all measured using the following scale: 1 (*never*), 2

Table 3.6

PIAAC Items Comprising Intrapersonal Factors

Factor	Item Code and Description
	In everyday life, how often do/did you usually…
Numeracy at Home	*H_Q03B* calculate prices, costs or budgets?
	H_Q03C use or calculate fractions, decimals or percentages?
	H_Q03D use a calculator - either hand-held or computer based?
	H_Q03F prepare charts, graphs or tables?
	H_Q03G use simple algebra or formulas ?
	H_Q03H use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques?
Technical Motivation at Home	*H_Q05C* use the internet to better understand various issues?
	H_Q05D use the internet to conduct transactions?
	H_Q05E use spreadsheets ?
	H_Q05G use a programming language to program/write code?
	During the last 12 months have you
Learning Motivation	*B_Q12A_T* participated in courses outside of program of studies?
	B_Q12A participated in open or distance education courses?
	B_Q12C attended any organized sessions for on-the-job training or training by supervisors or co-workers?
	B_Q12E participated in seminars or workshops?
	B_Q12G participated in work- or nonwork-related courses or private lessons, not already reported?
	B_Q02A _T1 Education or training in the last 12 months
	To what extent do the following statements apply to you
Learning Approach	*I_Q04B* When I hear or read about new ideas, I try to relate them to real-life situations to which they might apply.
	I_Q04D I like learning new things.
	I_Q04H When I come across something new, I try to relate it to what I already know.
	I_Q04J I like to get to the bottom of difficult things.
	I_Q04L I like to figure out how different ideas fit together.
	I_Q04M If I don't understand something, I look for additional information to make it clearer.
	In everyday life, how often do/did you usually…
Reading at Home	*H_Q01A* read directions or instructions?
	H_Q01B read letters, memos, or email?
	H_Q01C read newspapers or magazines?
	H_Q01D read articles in professional journals or scholarly publications?
	H_Q01E read books, fiction or non-fiction?
	H_Q01F manuals or reference materials?
	H_Q01G read financial statements?
	H_Q01H read diagrams, maps, or schematics?

(less than once a month), 3 (less than once a week but at least once a month), 4 (at least once a week but not every day), and 5 (every day).

Data Analysis

This study advanced the literature on the contribution of intrapersonal and environmental characteristics on adult numeracy achievement. One advantage of SEM is that observed variables and unobserved factors/latent variables can be combined into constructs that can test the relationships between each construct and numeracy proficiency. For this study, data analysis began with data cleaning and an examination of missing data. Confirmatory factor analysis (CFA) and structural equation modeling (SEM) followed to examine if the conceptual model was a good fit. When the model did not fit the data, CFA and SEM fit statistics provided exploratory information used to improve model fit without compromising the underlying theory.

Before providing further details on data analysis, it is necessary to describe some concepts specifically related to analyzing PIAAC data - plausible values, sampling weights, and replicate weights.

Numeracy Plausible Values

Adaptive testing means that all participants do not see identical items or take the same test. As a result, no participant is given a true score. Instead, each individual has 10 different plausible numeracy score values (PVNUM1 – PVNUM10) that are randomly selected from their individual estimated proficiency distribution. Estimated proficiency distributions take into account an individual’s accuracy in responses on the subset of numeracy assessment items and “how well other respondents from a similar background performed on the rest of the assessment item pool" (AIR PIAAC Team, 2016, p. 1). Accordingly, all 10 plausible numeracy values must be used in calculating numeracy proficiency.

"For accurate estimations involving proficiency scores," according to the AIR PIAAC Team (2016),

> calculations must account for both the sampling error component, and the variance due to imputation of the proficiency scores. To account for the sampling error component, you must use the final weight and the corresponding 80 replicate weights. To account for the imputation variance, you must use all ten plausible values (p. 1).

Accordingly, the final model was estimated using 10 plausible values as well as the sample weight. A final analysis with the application of 80 replicate weights was not possible due to lack of access of necessary computing capacity.

To analyze plausible values for numeracy, 10 separate datasets each containing one of the numeracy plausible values (e.g., PVNUM1, PVNUM2, etc.) were constructed. Another variable was created for each numeracy plausible value, which indicated if the participant's plausible value score fell within the top 10% or the bottom 90%. As each data set contained a range of different numbers, separate cutoff scores were calculated using SPSS (v. 24 & 25) at 90% for each plausible value set (e.g., PVNUM1, PVNUM2, etc.). Within each of the 10 data sets, scores below the 90th percentile were coded as a 0 and those in the top 10% were coded as 1. The 10 manually created data sets were retrieved through a list.dat file. Data analysis was conducted using M*plus* (*v*. 8.1). The weighted least squares (WLSMV) estimator imputation option was selected as it is appropriate for binary or ordered categorical dependent variables (Muthén & Muthén, 2017). Standard errors were calculated using the average of the squared standard errors

(Muthén & Muthén, 2017). Parameters were averaged from the 10 data sets. The final model was estimated using 10 plausible values and the sample weights (Rampey et al., 2016).

Sampling and Replicate Weights

Two different types of weights must be applied to the PIAAC data– a final sampling weight and replicate weights. The sampling weight is designed to make data representative of the U.S. population (AIR PIAAC Team, 2016). Using a simple random sample, every individual in a targeted population should be statistically independent and should have an equal chance of being selected for participation. Given the complexity of the PIAAC sample design, however, the resulting sample may have been dissimilar to a sample selected randomly. To account for sample selection method and non-response at each point of data collection (i.e., Screener, Background Questionnaire, or Direct Assessment), a final sampling weight (SPFWT0) is used to calibrate the participant data to the U.S. Census Bureau's 2012 American Community Survey population benchmarks. These weights account for any sampling error and facilitate variance estimation using the replication approach.

As mentioned previously, a lack of access to a supercomputer prevented an analysis that included the application of the 80 replicate weights (SPFWT1-SPFWT80). Replicate weights should be applied given the PIAAC's clustered sampling approach which differs from traditional sample variance estimates that assume simple random sampling (Rampey et al., 2016; Rust & Rao, 1996). As a result, standard errors may be underestimated.

Descriptive Statistics

Given the complexities that result from using a dual-frame complex sampling method and an adaptive competency assessment, calculating descriptive statistics was not straightforward. Not all participants were presented with the numeracy assessment and, of those that did take the numeracy assessment, they may have received different questions depending on their performance on their numeracy testlets. Therefore, accurate estimates for proficiency scores (e.g., numeracy proficiency) must have applied the sample weights, the replicate weights, and all 10 plausible values. To ensure that researchers correctly apply sampling weights and take into account the plausible values, OECD created a data analysis tool called the International Data Explorer (IDE). Accordingly, the IDE was used to gather descriptive statistics. (This tool can be accessed at https://nces.ed.gov/surveys/international/ide/.)

Descriptive statistics obtained using the IDE included the percent of the population exhibiting each characteristic, average scale scores, and standard errors. As data were collected from a sample used to estimate group/subgroup performance "rather than the values that could be calculated if every person in the nation answered every question on the instrument" (Rampey et al., 2016, p. C-7), standard errors represented test statistic uncertainty. The IDE did not provide frequencies (i.e., *n*).

Descriptive statistics are provided for the items specified in Tables 3.3 to 3.6 and are grouped by those who performed in the top 10% compared to those who did not. Table 3.7 shows the percentage of the U.S. population within each of the PIAAC proficiency levels. Table 3.8 provides the statistics that resulted from grouping into two proficiency levels: (a) *Bottom 90%*, resulted from collapse the values of Literacy related to non-response, Below Level 1, Level 1, Level 2, and Level 3, and (b) *Top 10%* resulted from collapsing the values of Level 4 and Level 5.

Table 3.7

Percentage of Population and Average Score at Each Proficiency Level (PVNUM)

PIAAC Categories	%	SE	M	SE
Literacy related to non-response	‡	†	‡	†
Below Level 1	8%	(0.5)	147	(1.9)
Level 1	19%	(0.7)	204	(0.5)
Level 2	34%	(0.9)	252	(0.4)
Level 3	29%	(0.9)	299	(0.5)
Level 4	9%	(0.6)	343	(0.7)
Level 5	1%	(0.2)	‡	†

Note. † Not applicable. ‡ Reporting standards not met. Data gathered using the PIAAC International Data Explorer.

Table 3.8

Numeracy Proficiency Levels (PVNUM) Used to Create New Variables

New Variable	PIAAC Categories	%	SE	M	SE
Bottom 90%	Literacy related to non-response, Below Level 1, Levels 1, 2, & 3	90	(0.7)	247	(1.0)
Top 10%	Levels 4 & 5	10	(0.7)	347	(0.9)

Note. Data gathered using the PIAAC International Data Explorer.

Data Cleaning

As stated previously, the PIAAC 2012/2014: U.S. National Supplement Public Use Household Data was used. The first step in data cleaning was to eliminate individuals who were not between the ages of 16 and 65 according to the variable AGE10LFSEXT. Second, as we were only including adults who had been employed in the last 12 months in the sample, only those who indicated yes = 1 to PAIDWORK12 were retained (resulting in a final sample n = 5,862). To provide researcher transparency, the following section will describe changes that were made to the dataset in order to facilitate data analysis.

Recoding

After reducing the data file to the sample meeting the study criteria, further data cleaning was necessary. Some items were reverse coded to match intuitive thinking to aid with the interpretation of results. It was also necessary to dummy code items that had three or more categorical responses into new binary items. Finally, in order to maximize usable data, valid skips based on a response to a prior question were recoded to reflect known values. Table 3.9 provides a summary of the categorical covariates after recoding.

Reverse coding. In some instances, PIAAC responses were reversed to correspond with intuitive reasoning. For example, the binary Learning Motivation items were reverse coded (e.g., B_Q02A; B_Q12A_T; B_Q12A, C, E, G) with a *no* response served as the reference group (no = 0). Additionally, a *no* responses to the learning disability (I_Q08USX3) item and the vision problems item (I_Q08USX1) were also recoded as the reference group (no = 0). Additionally, the language item (NATIVELANG) was reverse coded so that the reference group was taken in the respondents' native language (in same language = 0) when the survey was completed.

Dummy coding. When a categorical variable had more than two response items, dummy coding was necessary for comparing the different groups based on responses. When using dummy coding, the number of dummy codes per variable should always be $k - 1$ (where k is the number of response options). For example, the race item (RACETHN_4CAT) was recoded into three new variables to HISPANIC, BLACK, and

OTHERRACE with as White race serving as the reference (White = 0). Another item measuring employment status (C_D05) was recoded into two new variables with employment as the reference category (employed = 0): UNEMPLOYED and OUTOFWORKFORCE.

One variable, the item measuring persistence (B_Q03A), required two steps when dummy coding. First, valid skips on B_Q03A resulting from an affirmative response to a prior item asking if they were studying for a formal degree or certificate (when yes = 1 on B_Q02A) were recoded to a new response (presently studying = 3) to minimize missing data. Next, a new dummy variable UNCOMPLETED was created in which an affirmative response, which indicated discontinuation of a degree or enrolled in education, were coded as a value of 1. A second dummy coded variable (PRESSTUDYING) was created to reflect current work on a degree in which studying for a degree was a value of 1. The reference category (coded = 0) was persisted until earning a degree. After data cleaning and recoding were completed, missing data were inspected.

Missing Data

Although data can be missing for various reasons, all missing data, regardless of the reason, is treated the same in SEM and should be minimized when possible. In the PIAAC dataset, different codes were assigned for each of the following reasons: refusal to answer, not stated or inferred, unknown/unsure, or valid skip resulting from a previous answer to a routing question. In some instances, however, a response coded as a valid. skip actually reflected a known value. As missing data can significantly impact data analysis, it was important to minimize the missingness whenever possible

Table 3.9

Coding of Categorical Covariates

Variable Code	Description/Recode	Values
J_Q06BUS	Mother- Ed	1= Less than high school diploma 2 = H.S. diploma with some college 3= college degree or higher
J_Q06A	Mother- Immigrant	1= Born in U.S. 2 = Not born in U.S.
J_Q07BUS	Father- Ed	1= Less than high school diploma 2 = H.S. diploma with some college 3= college degree or higher
J_Q07A	Father-Immigrant	1= Born in U.S. 2 = Not born in U.S.
C_D05[1]	UNEMPLOYED	0 = Employed or out of workforce 1= Unemployed
	OUTOFWORKFORCE	0 = Employed or unemployed 1= Out of Workforce
GENDER_R	Gender	1= Male 2 = Female
RACETHN_4CAT[1]	BLACK	0 = Not Black 1 = Black
	HISPANIC	0 = Not Hispanic 1 = Hispanic
	OTHERRACE	0 = White, Black, Hispanic 1 = All other races
NATIVELANG	Native Language	0 = Test given in native language 1 = Test not same as native language
I_Q08USX3[2]	Learn Disability	0 = Does not have a learning disability 1 = Has a learning disability
I_Q08USX1[2]	Vision Problem	0 = Does not have difficulty seeing print 1= Has difficulty seeing print
B_Q03A[1]	UNCOMPLETED	0 = Completed/presently studying 1 = Discontinued degree
	PRESATTEND	0 = Completed/discontinued degree 1 = Presently working on a degree
B_Q12A_T	Courses outside program	0 = Courses not taken outside program in last 12 months 1= Courses taken outside studies

Note. [1]Recoded as dummy variables; the dummy code is provided in the second column in all capitals. [2]Variables reverse coded from the original as stated.

The first step in tending to missing data was, therefore, to reduce missingness coded as a valid skip when the actual value was known. Responses to some individual questions or groups of questions were coded as valid skips because the respondent initially indicated that they never did a task on a previous routing question. In these instances, the valid skips on the subsequent item that met these criteria were recoded to *never* (value = 1). For example, although participants who responded that they did not use a computer in their job (G_Q04) were coded by PIAAC as a valid skip for Technical/Computer Skill Use at work items (G_Q05C, D, E, G), these responses were recoded to *never* for the latter items. Similarly, participants who indicated they had not ever used a computer (H_Q04A) or did not have experience using a computer in everyday life (H_Q04B), were recoded from valid skip to *never* (value = 1) for Technical/Computer Skill Use at home items (H_Q05C, D, E, G). One additional item measuring learning from co-workers or supervisors (D_Q13A) had skip items that were recoded. Participants who were valid skips on D_Q13A because they indicated self-employed (value = 2 to item D_Q04) with no employees (value = 2 to item D_Q07A), were recoded to *never* learning from co-workers or supervisors (value = 1).

The second step was to consolidate the remaining values for missing data into one singular code for data analysis. As mentioned previously, the PIAAC dataset utilized numerous codes for missing values (e.g., 6, 7, 8, 9, 96, 97, 98, 99, 996, 997, 998, 999, 9994, 9996, 9997, 9998, 9999). As some items had valid responses that also used codes of 6, 7, 8, or 9, changes to consolidate all missing variables into one code (e.g.,-99) could not be made to the entire dataset at one time. Accordingly, all categorical variables with response values greater 96 were recoded to a singular new value that consolidated missing data (-99). Next, the dataset was checked for any remaining items that used values of 6, 7, 8, or 9 for missing data, which were recoded to -99.

SPSS was used to obtain weighted percentages of missing data after completion of the previously described data cleaning and recoding process. Table 3.10 reports weighted percentages of missing data for the covariate items. Tables 3.11 and 3.12 report weighted percentages of missing data for the environmental and intrapersonal covariate and factor items, respectively.

Table 3.10

Covariate Items: Percent Missing After Data Cleaning and Recoding

Covariate	Item Code and Description	% Missing[1]
Mother- Ed	J_Q06BUS Mother highest level of education	1.3%
Mother- Nat	J_Q06A Mother/female guardian born in country	0.1%
Father- Ed	J_Q07BUS Father highest level of education	3.6%
Father-Nat	J_Q07A Father/male guardian born in country	0.7%
Cultural Capital	J_Q08 # books in home at 16 years old	0.2%
Education	EDCAT6 Highest level of formal education	0.1%
Employment[2]	C_D05 Employment status	0.0%
Income[5]	D_Q18A_T Annual net income by quintile (derived)	17.3%
Gender	GENDER_R	0.0%
Race[3]	RACETHN_4CAT Race/ethnicity (4 categories)	0.2%
Age	AGEG10LFS_T Age groups in 10-year bands	0.0%
Native Lang.	NATIVELANG Test is in native language	0.0%
Health	I_Q08 health status	0.1%
Learn Disability	I_Q08USX3 diagnosed having a learning disability	0.1%
Vision Problem	I_Q08USX1 difficulty seeing the words and letters	0.1%
Persistence[4]	B_Q03A leave degree program before completing	0.0%

Note. [1]Weighted percentages reported. [2]Employment was dummy coded into two binary variables: UNEMPLOYED and OUTOFWORKFORCE. [3]Race was dummy coded into three binary variables: HISPANIC, BLACK, and OTHERRACE. [4]Persistence was dummy coded into two binary variables: UNCOMPLETED AND PRESSTUDYING. [5]Income will not be included in the CFA or SEM models because of a high level of missingness.

Table 3.11

Environmental Factor Items: Percent Missing Data After Data Cleaning and Recoding

Factor	Item Code and Description	% Missing[1]
Numeracy at Work	G_Q03B calculate prices, costs or budgets	0.0%
	G_Q03C use or calculate fractions, decimals or %	0.0%
	G_Q03D use a calculator	0.0%
	G_Q03F prepare charts, graphs or tables	0.1%
	G_Q03G use simple algebra or formulas	0.1%
	G_Q03H use more advanced math or statistics	0.1%
Reading at Work	G_Q01A read directions or instructions	0.0%
	G_Q01B read letters, memos, or email	0.0%
	G_Q01C read newspapers or magazines	0.0%
	G_Q01 read professional journals/scholarly publications	0.0%
	G_Q01E read books, fiction or non-fiction	0.0%
	G_Q01F manuals or reference materials	0.0%
	G_Q01G read financial statements	0.0%
	G_Q01H read diagrams, maps, or schematics	0.0%
Technical Skill Use at Work	G_Q05C[2] use the internet to collect information	0.0%
	G_Q05D[2] use the internet to conduct transactions	0.0%
	G_Q05E[2] use spreadsheets	0.0%
	G_Q05G[2] use computer programming language	0.0%
Learning at Work	D_Q13A[3] learning from co-workers or supervisors	10.0%
	D_Q13B learning-by-doing from the tasks you perform	10.1%
	D_Q13C keeping up to date with products or services	10.0%
Job Culture	F_Q02A sharing work-related info with co-workers	0.0%
	F_Q03A planning your own activities	0.1%
	F_Q03B planning the activities of others	0.1%
	F_Q03C organizing your own time	0.1%
	F_Q05A simple problems	0.1%
	F_Q05B complex problems	0.1%

Note. [1] Weighted percentages reported. [2]After recoding as “never” for individuals who indicated they did not use a computer at work. [3]After recoding as “never” for self-employed individuals who do not have employees.

Table 3.12

Intrapersonal Factor Items: Percent Missing Data After Data Cleaning and Recoding

Factor	Item Code and Description	% Missing[1]
Numeracy at Home	H_Q03B calculate prices, costs or budgets	0.0%
	H_Q03C use or calculate fractions, decimals or percentages	0.0%
	H_Q03D use a calculator	0.0%
	H_Q03F prepare charts, graphs or tables	0.1%
	H_Q03G use simple algebra or formulas	0.1%
	H_Q03H use more advanced math or statistics	0.0%
Technical Skill Use at Home	H_Q05C[2] use the internet to better understand various issues	0.0%
	H_Q05D[2] use the internet to conduct transactions	0.0%
	H_Q05E[2] use spreadsheets	0.0%
	H_Q05G[2] use a programming language	0.0%
Learning Motivation	B_Q12A_T participated in courses outside of studies	2.9%
	B_Q12A participated in open or distance education courses	3.0%
	B_Q12C attended on-the-job training	3.0%
	B_Q12E participated in seminars or workshops	2.9%
	B_Q12G participated in other courses or private lessons	3.0%
	B_Q02A _T1 Education or training in the last 12 months	0.0%
Learning Approach	I_Q04B relate ideas to real-life situations	0.1%
	I_Q04D like learning new things.	0.0%
	I_Q04H try to relate new info to what I already know	0.0%
	I_Q04J like to get to the bottom of difficult things	0.0%
	I_Q04L like to figure out how different ideas fit together.	0.0%
	I_Q04M If I don't understand, I look for additional info	0.0%
Reading at Home	H_Q01A read directions or instructions	0.1%
	H_Q01B read letters, memos, or email	0.0%
	H_Q01C read newspapers or magazines	0.0%
	H_Q01D read professional journals/scholarly publications	0.1%
	H_Q01E read books, fiction or non-fiction	0.0%
	H_Q01F manuals or reference materials	0.0%
	H_Q01G read financial statements	0.0%
	H_Q01H read diagrams, maps, or schematics	0.0%

Note. [1]Weighted percentages reported. [2]After recoding as *never* for individuals who indicated they did not use a computer at home.

As missing data may bias CFA and SEM results, data were examined using Little's Missing Completely At Random (MCAR) test (Little & Rubin, 2002). Table 3.13 presents the results from the MCAR test. A nonsignificant value (i.e., $p > .05$) indicates the data is MCAR and is preferred. The results showed nonsignificant values for all individual covariates except the income measure. All of the factors had nonsignificant MCAR values, except the Learning Approach factor. For the most part, the amount of missing data in this study does not appear to be problematic as "a few missing values, such as < 5% in the total data set, may be of little concern" (Kline, 2016, p. 83).

Table 3.13

Little's MCAR Test Results (with EM Correlations)

Factor	$\chi 2$	*df*	*p*
Numeracy at Work	7.06	3	.070
Reading at Work	23.87	27	.648
Technical Skill At Work	NA	NA	NA
Learning at Work	4.23	5	.517
Job Culture	32.63	30	.339
Numeracy at Home	22.12	23	.513
Technical Skill At Home	NA	NA	NA
Learning Motivation[1]	-	-	-
Learning Approach	43.82	10	.000
Reading at Home	19.90	24	.702
Environmental factor			
without covariates	712.39	404	.000
with covariates added	5080.81	929	.000
Intrapersonal factor			
without covariates	557.27	465	.002
with covariates added	612.06	510	.001

Note. [1]Cannot test categorical variables.

Larger percentages of missing data, however, are more concerning, especially if the reason for the data loss is not random. The income covariate was not included in the model giving the level of missingness and was only reported descriptively. When examining the second order factors, however, significant values indicated that data were not missing completely at random. This is not surprising given the large sample size that makes patterns of missingness detectable.

Confirmatory Factor Analysis

After cleaning and recoding, CFA was conducted using M*plus* (*v*.8.1) using the WLSMV estimator to assess the underlying structure of the latent factors. The WLSMV estimator is robust to nonnormality and non-independent observations. The first variable in each first-order factor was used as a marker variable, and all other paths were freely estimated.

The goodness-of-fit statistics that were used to test the CFA include chi-square (χ^2), Comparative Fit Index (CFI: Bentler, 1990), Root Mean Square Error of Approximation (RMSEA; Steiger & Lind, 1980), Standardized Root Mean Square Residual (SRMR), and Tucker-Lewis Index (TLI; Tucker & Lewis, 1973). The following criteria were used for assessing model fit: nonsignificant $\chi 2$, CFI $\geq$ .95, RMSEA $\leq$ .06, SRMR $\leq$ .08, and TLI $\geq$ .95 (Brown, 2015; Browne & Cudeck, 1992; Hu & Bentler, 1999). Some argue these model fit statistics are too stringent, asserting that CFI and TLI values from .90 to .95 may also indicate an acceptable fit (Brown, 2015). Standardized results were provided for CFA results and SEM results. Exploratory approaches, such as questioning theoretical assumptions or identify localized areas of strain/misfit by examining residuals, modification indices, and/or unnecessary parameters, were be utilized to improve model fit (Brown, 2015).

Structural Equation Modeling

The resulting CFA was used in a second-order structural equation modeling (SEM). SEM is appropriate to examine relationships among factors with other variables (Schreiber, Nora, Stage, Barlow, & King, 2006). Specifically, the SEM in this study examined the relationships between environmental variables, intrapersonal variables, and numeracy proficiency as a binary outcome (with those scoring below the 90^{th} percentile coded as the reference group). Fit of the SEM models with sample weights was assessed using chi-square (χ^2), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), and Tucker-Lewis Index (TLI) with the same criteria described in the CFA section. First, fit was examined using only one set of plausible values. Next, fit for the SEM was established using all sets of plausible values and application of the sample weights.

Summary

This chapter described the research questions and provided a diagram of the specified SEM model that was tested. A description of the participants, data collection process, specific items chosen, and method of data analysis was provided. Pertinent literature justified the methodology. Any necessary modifications to the model and results of the data analysis will be presented in Chapter Four.

CHAPTER FOUR

Results

Introduction

This chapter provides the results from data analysis. First descriptive statistics will be presented. Next, CFA steps and results will be provided. As a result of the CFA, a post hoc model is presented. The chapter concludes with the SEM analysis followed by a description of the findings from the post hoc model.

Descriptive Statistics

Given the advantages of descriptive statistics provided by OECD's International Data Explorer (IDE), descriptive data were calculated using the entire adult (age 16-65) sample. As explained in the data analysis section of Chapter Three, the most detailed descriptive data can be gathered using the IDE. Benefits of using the IDE tool is that the IDE output provides (a) weighted summary statistics to reflect the percentage of the population meeting item criteria, (b) average numeracy scores for each group per item, and (c) associated standard error terms for each statistic. As the OECD does not explain how these average numeracy scores are calculated, weighted descriptive statistics calculated outside of the IDE using a data analysis tool such SPSS, M*plus*, or SAS will only produce percentages within each group; information on average numeracy scores and associated standard errors are not calculated. One disadvantage of using the IDE, however, is that population summary information by proficiency level can only be provided for the entire adult sample (*n* = 7,917). As stated previously, the sample used for the CFA and SEM analysis (n = 5,862) included only those adults who indicated employment within the past 12 months.

This decision was further supported by a comparison of descriptive data generated by IDE using the entire sample and descriptive data for the employed sample using SPSS that demonstrated very minor differences. For example, SPSS was used to calculate descriptive percentages (with an application of sample weights) using the employed sample for the top 10% performers in numeracy and bottom 90% of the employed sample for approximately 20 items. A comparison of the percentages for the entire adult sample (i.e., IDE output) and the employed sample (i.e., SPSS output) indicated differences in population percentages that were less than 3%. The only exceptions were items that included direct measures of employment or items in which valid skips were recoded. In these instances, differences were noted in the tables.

Three items should be noted for the descriptive statistics reported in Tables 4.1 to 4.29. First, the sources of the data were U.S. Department of Education, National Center for Education Statistics; Statistics Canada and Organization for Economic Cooperation and Development; Program for the International Assessment of Adult Competencies (PIAAC), Literacy, Numeracy, and Problem Solving TRE Assessment. Second, row percentages may not sum to 100 because of rounding. Third, some apparent differences between estimates may not be statistically significant.

Environmental Characteristics

Summary tables are provided for the environmental covariate items followed by environmental factors. Although some participant characteristics are not theorized to contribute to numeracy (e.g., marital status or children), characteristics such as these are reported elsewhere in the literature or are items of interest and, therefore, have been reported in this section for descriptive purposes only.

Family of origin. Although there were some similarities between the parent education levels of the highest performers in numeracy and of those who were less proficient, talented individuals were more likely to have a parent with a college degree. Almost half of the individuals within both groups had parents who graduated from high school and may have attended college (see Table 4.1). Average numeracy competency for both groups also increased, on average, with increasing levels of parent education. Individuals in the top 10%, however, were approximately twice as likely to have parents who earned a college degree (53%, SE = 1.3) compared to individuals within the lower proficiency group (26%, SE = 0.9).

Although a similar percentage from both numeracy proficiency groups had a mother born in the United States, significant differences (p = .003) were noted in the frequency of paternal immigrants. For example, 85% (SE = 2.9) of highly numerate individuals had fathers born in the United States compared to 78% (SE = 0.6) of those with lower numeracy proficiency (see Table 4.2). For the high numeracy proficiency group, however, average numeracy scores appeared to be unrelated to parent immigrant status (M = 347, SE = 1.1 and M = 348, SE = 2.1-2.6). Interestingly, only individuals in the lower proficiency group who had an immigrant mother or father had lower numeracy proficiency scores (M = 231, SE = 3.0), on average, than those whose mother or father was born in the United States (M = 251; M = 252, SE = 1.1).

Table 4.1

Parents' Highest Level of Education by Numeracy Proficiency Level

Numeracy Competency	< High school diploma				High school diploma/some college but no degree				College degree or higher (Associate, Bachelor, Doctorate)			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Mother/Guardian (J_Q06BUS)												
Bottom 90%	222	(2.2)	29	(0.8)	253	(1.2)	47	(0.9)	267	(1.2)	24	(0.8)
Top 10%	‡	†	7	(1.3)	346	(1.5)	46	(3.1)	348	(1.6)	47	(3.0)
Father/Guardian (J_Q07BUS)												
Bottom 90%	225	(2.0)	29	(0.9)	254	(1.3)	45	(1.0)	267	(1.5)	26	(0.9)
Top 10%	‡	†	7	(1.6)	347	(1.6)	40	(2.7)	348	(1.3)	53	(2.7)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.2

Mother and Father Born in United States by Numeracy Proficiency Level

Numeracy Competency	Yes				No			
	Avg.	SE	%	SE	Avg.	SE	%	SE
Mother/Guardian (J_Q06A)								
Bottom 90%	251	(1.1)	79	(0.6)	231	(3.0)	21	(0.6)
Top 10%	347	(1.1)	82	(2.3)	348	(2.1)	18	(2.3)
Father/Guardian (J_Q07A)								
Bottom 90%	252	(1.1)	78	(0.6)	231	(3.0)	22	(0.6)
Top 10%	347	(1.1)	85	(2.0)	348	(2.6)	15	(2.0)

Differences in the access to books in teen years were associated with differences in numeracy performance and were especially true for individuals from families possessing the fewest books. Only 4% (*SE* = 1.0) of the most proficient individuals reported fewer than 10 books in their home, whereas 21% (*SE* = 4.6) of the less proficient group had few books in their home (see Table 4.3). Slightly over 30% of both groups of participants reported having 26 to 100 books in their home. Although 21% (*SE* = 2.3) of highly numerate participants recalled having over 200 books in their home, only 8% (*SE* = 0.5) of those within the lower numeracy proficiency group had more than 200 books. For those in the bottom 90%, however, increased books in the home at age 16 appeared to have been associated with increased numeracy proficiency, on average. It is possible that there was is a threshold effect in that the having over 100 books in the home had little, if any, increasing positive effect on numeracy proficiency.

Education. Increasing levels of education were associated with higher numeracy proficiency. Highly numerate individuals were significantly ($p < .001$) more likely to reported a terminal-level bachelor's degree (35%, *SE* = 3.3) compared to 15% (*SE* = 0.6) of those in lower proficiency group (see Table 4.4). Furthermore, 43% (*SE* = 0.5) of individuals with lower numeracy proficiency had a terminal high school diploma compared to 20% (*SE* = 2.1) of the highly numerate individuals. Average scores also increased for both groups with higher levels of education.

Marriage/long-term relationships and children. Although it is not theorized that long-term relationships/marriage or children impact numeracy development, these items are reported descriptively to be consistent with other literature. From the IDE analysis it would appear that a majority of adults were living with their spouse or partner (see Table 4.5). Once participants who indicated a living household size of one were recoded as not living with a spouse or partner, however, a different trend emerged. Of the employed sample, only 33% to 40% of individuals indicated residing with a spouse/partner. In both groups, those who did not live with spouse or partner had lower average numeracy

Table 4.3

Number of Books in Home at Age 16 (J_Q08) by Numeracy Proficiency Level

Numeracy Competency	10 books or less				11 to 25 books				26 to 100 books				101 to 200 books				201 to 500 books				> 500 books			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	218	(2.2)	21	(0.6)	236	(2.2)	20	(0.7)	255	(1.5)	32	(0.7)	267	(1.9)	15	(0.6)	270	(2.6)	8	(0.5)	268	(3.4)	4	(0.3)
Top 10%	‡	†	4	(1.0)	‡	†	10	(1.6)	346	(1.9)	31	(2.2)	348	(2.4)	24	(2.3)	349	(1.9)	21	(2.3)	350	(3.6)	11	(1.9)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.4

Highest Education Level (EDCAT6) by Numeracy Proficiency Level

Numeracy Competency	Lower secondary or less (ISCED 1,2, 3C short or less)				Upper secondary (ISCED 3A-B, C long)				Post-secondary, non-tertiary (ISCED 4A-B-C)				Tertiary - professional degree (ISCED 5B)				Tertiary - bachelor degree (ISCED 5A)				Tertiary - master/research degree (ISCED 5A/6)			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	210	(1.8)	15	(0.3)	241	(1.4)	43	(0.5)	247	(2.8)	9	(0.5)	262	(2.6)	9	(0.5)	276	(1.5)	15	(0.6)	283	(2.0)	8	(0.3)
Top 10%	‡	†	1	(0.5)	344	(2.4)	20	(2.1)	‡	†	5	(1.3)	‡	†	8	(1.4)	348	(2.0)	35	(3.3)	350	(1.7)	30	(2.8)

Note. † Not applicable. ‡ Reporting standards not met.

scores than those that did live with their spouse or partner. A majority of both groups indicated having children (see Table 4.6). A significantly smaller percentage ($p < .001$), however, of the highly numerate individuals had children/stepchildren (55%, *SE* = 2.9) compared to 66% (*SE* = 0.6) of those with lower numeracy levels. Although the average number of children could not be accessed using the IDE, it was calculated (with population weights) using SPSS. The highest proficiency group (*M* = 2.17, *SD* = 0.95) had fewer children, on average, compared to those in the bottom 90% of numeracy competency (*M* = 2.35, *SD* = 1.02). When including adults without children (i.e., those who indicated number of children = 0), the difference between groups was accentuated (*M* = 1.18, *SD* = 1.29 vs. *M* = 1.54, *SD* = 1.39).

Table 4.5

Living with Spouse/Partner (J_Q02A) by Numeracy Proficiency Level

Numeracy Competency	Yes				No			
	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	251	(1.3)	65	(0.8)	240	(1.7)	35	(0.8)
Top 10%	348	(1.2)	78	(2.5)	346	(2.0)	22	(2.5)
Employed Bottom 90%[1]	-	-	40	-	-	-	60	-
Employed Top 10%[1]	-	-	33	-	-	-	67	-

Note. [1]Recoded valid skips (those who indicated household size = 1) as not living with a spouse/partner. - Unable to be calculated.

Table 4.6

Had Children/Stepchildren (J_Q03A) by Numeracy Proficiency Level

Numeracy Competency	Yes				No			
	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	244	(1.2)	66	(0.6)	253	(1.6)	34	(0.6)
Top 10%	346	(1.3)	55	(2.9)	349	(1.7)	45	(2.9)

Employment. Individuals with the highest numeracy levels were more likely to be employed. Although most adults were employed, a significantly larger percentage (86%, *SE* = 1.5, *p* < .001) of highly numerate individuals were employed at the time of the survey compared to (72%, *SE* = 0.7) participants with lower numeracy proficiency (see Table 4.7). Accordingly, a smaller percentage of participants with the highest numeracy proficiency were unemployed or out of the labor force. There was a much larger difference in average numeracy scores for the lower proficiency group between employed individuals (*M* = 253, *SE* = 1.2) and individuals out of the labor force (*M* = 232, *SE* = 1.9) compared to the difference between employed individuals (*M* = 348, *SE* = 1.20) and those out of the labor force (*M* = 345, *SE* = 3.0) at the highest proficiency levels. As the percentages of unemployed or individuals out of the labor force were significantly different for the employed sample (*n* = 5,862) used in the CFA and SEM for this study, descriptive information for this sample were calculated using SPSS (see Table 4.7).

Table 4.7

Employment Status at Time of the Survey (C_D05) by Numeracy Proficiency Level

	Employed				Unemployed				Out of the labor force			
Numeracy Competency	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Entire Sample (IDE)												
Bottom 90%	253	(1.2)	72	(0.7)	233	(2.0)	7	(0.2)	232	(1.9)	20	(0.7)
Top 10%	348	(1.0)	86	(1.5)	‡	†	3	(0.7)	345	(3.0)	11	(1.4)
Employed Sample												
Bottom 90%	-	-	90	-	-	-	5	-	-	-	5	-
Top 10%	-	-	93	-	-	-	2	-	-	-	5	-

Note. † Not applicable. ‡ Reporting standards not met. - Unable to be calculated.

The type of employment differed by numeracy status as well. Although 74% (*SE* = 2.4) of the highly numerate group were employed in skilled jobs, only 41% (*SE* = 0.8) of individuals in the lower numeracy group worked in a skilled job (see Table 4.8). Significantly fewer of the top numeracy group worked in semi-skilled white-collar (16%, *SE* = 1.8, $p < .001$) or semi-skilled blue-collar jobs (8%, *SE* = 1.6, $p < .001$) compared to the lower numeracy group (32%, *SE* = 0.6 and 17%, *SE* = 0.6), respectively. This variable is reported for descriptive purposes only and was not included in the SEM because it was theorized that that job type would be highly related to income level and result in multicollinearity.

Income. Participants' income levels also differed by numeracy proficiency. Significantly more ($p < .001$) of the highest skilled numeracy group (45%, *SE* = 3.5) reported earning an income in the top quintile compared to only 16% % (*SE* = 3.5) of the lower proficiency group (see Table 4.9). As almost 50% of U. S. participants did not report their income, these results should be interpreted with caution. It should be noted, however, that the percentages changed little when examining only the employed sample. Given the large degree of missingness, this item was not included in the CFA or SEM models.

Work flexibility. Another aspect of the work environment that PIAAC assessed included participants' perceptions of the flexibility of their jobs (see Table 4.10). Highly numerate individuals had more flexibility in their working environment than the less numerate group in multiple ways. Their responses indicated a *high extent* or *very high extent* of flexibility in their sequence of tasks (59% to 43%), how to do the work (54% to 44%), and their working hours (36% to 26%). These characteristics were not theorized to

Table 4.8

Occupational Classification (ISCOSKIL4) by Numeracy Proficiency Level

Numeracy Competency	Skilled				Semi-skilled white-collar				Semi-skilled blue-collar				Elementary occupations			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	268	(1.1)	41	(0.8)	243	(1.6)	32	(0.6)	240	(2.1)	17	(0.6)	224	(3.1)	10	(0.4)
Top 10%	348	(1.3)	74	(2.4)	345	(2.4)	16	(1.8)	‡	†	8	(1.6)	‡	†	2	(0.9)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.9

Annual Income Percentile Rank (D_Q18AT) by Numeracy Proficiency Level

Numeracy Competency	Lowest quintile				Next lowest quintile				Mid-level quintile				Next to highest quintile				Highest quintile				Missing
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	%
Entire Sample (IDE)																					
Bottom 90%	243[1]	(2.6)	21[1]	(0.8)	236[1]	(2.2)	21[1]	(0.9)	251[1]	(1.8)	21[1]	(0.9)	266[1]	(1.9)	20[1]	(0.8)	276[1]	(2.6)	16[1]	(0.9)	-
Top 10%	‡	†	10[1]	(1.9)	‡	†	10[1]	(1.7)	347[1]	(3.9)	14[1]	(2.6)	347[1]	(1.9)	20[1]	(2.5)	350[1]	(1.7)	45[1]	(3.5)	-
Employed Sample																					
Bottom 90%	-	-	17	-	-	-	17	-	-	-	17	-	-	-	16	-	-	-	14	-	18
Top 10%	-	-	7	-	-	-	9	-	-	-	13	-	-	-	19	-	-	-	38	-	13

Note. 1% of resported no income. † Not applicable. ‡ Reporting standards not met. [1]The item response rate is below 85 percent. Missing data have not been explicitly accounted for.

Table 4.10

Work Flexibility of Current Job by Numeracy Proficiency Level

Numeracy Competency	Not at all				Very little				To some extent				To a high extent				To a very high extent			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Sequence of tasks (D Q11A)																				
Bottom 90%	230	(3.0)	10	(0.6)	245	(2.5)	14	(0.6)	254	(1.8)	33	(1.0)	260	(2.1)	22	(0.8)	261	(2.1)	21	(0.8)
Top 10%	‡	†	3	(1.1)	‡	†	8	(1.5)	348	(2.4)	29	(2.4)	347	(1.9)	27	(2.5)	348	(1.9)	32	(2.6)
How to do the work (D_Q11B)																				
Bottom 90%	226	(3.2)	9	(0.6)	248	(2.5)	15	(0.7)	258	(1.7)	32	(0.9)	259	(2.1)	23	(0.7)	254	(2.4)	21	(0.8)
Top 10%	‡	†	1	(0.8)	‡	†	9	(1.7)	347	(2.2)	34	(3.0)	348	(1.7)	28	(2.6)	348	(1.8)	28	(2.2)
Speed of work (D_Q11C)																				
Bottom 90%	232	(4.2)	7	(0.5)	252	(2.8)	13	(0.6)	257	(2.0)	34	(0.8)	258	(2.1)	24	(0.8)	249	(2.2)	22	(0.9)
Top 10%	‡	†	2	(0.8)	346	(3.4)	11	(1.5)	348	(2.0)	37	(2.6)	347	(2.4)	27	(3.0)	349	(2.2)	23	(2.2)
Working hours (D_Q11D)																				
Bottom 90%	239	(2.0)	26	(1.0)	255	(2.2)	20	(0.9)	259	(2.1)	28	(0.9)	259	(3.0)	13	(0.7)	259	(2.8)	13	(0.7)
Top 10%	‡	†	10	(2.2)	348	(2.5)	19	(2.2)	347	(2.2)	34	(3.0)	348	(2.4)	20	(2.5)	347	(2.8)	16	(1.9)

Note. † Not applicable. ‡ Reporting standards not met.

impact numeracy proficiency per se but are recorded as a point of comparison with prior research discussed in the literature review.

Numeracy at work. A greater percentage of the most numerically proficient individuals reported more frequent use of most numeracy skills at work compared to those at lower proficiency levels (see Table 4.11). The most proficient group reported the following skills were used more than once a week: calculator use (65%), fractions/percentages (61%), simple algebra or formulas (47%), calculating costs or budgets (40%), preparing charts/graphs (32%), and advanced math/statistics (13%). For comparison, the percentage of the lower proficiency group reported they used these skills more than once a week: calculator use (56%), fractions/percentages (48%), simple algebra or formulas (26%), calculating costs or budgets (40%), preparing charts/graphs (20%), and advanced math/statistics (6%). The largest relative differences between groups were in math skills that are traditionally taught in high school and beyond (e.g., algebra, advanced math, and statistics). The skill used least frequently was advanced math and statistics, with 61% of the most proficient group indicating they never use those skills at work. Interestingly, the highest average numeracy proficiency score typically peaked for individuals in the middle of the table (i.e., those reported skill use on a monthly to weekly level), and the mean numeracy score either remained the consistent or decreased for individuals reporting more frequent skill use at work. This finding was consistent for both groups.

Reading at work. A larger percentage of the highest numeracy group reported using some reading skills at work more frequently compared to the lower numeracy group (see Table 4.12). When comparing reading at work for the more numerically skilled versus. the less numerically skilled, the top 10% read the following more than once a week: directions or instructions (86% vs. 68%), newspapers or magazines (58% vs. 44%), professional journals (39% vs. 27%), or diagrams, maps, or schematics (37% vs. 31%). The same trend did not appear in the use of reading skills more than once a week for the most highly skilled group versus the less numerically skilled: reading directions/instructions (67% vs. 69%); reference manuals (39% vs. 42%); and reading books (14% vs. 18%). Interestingly, for the lower numeracy group, average numeracy scores significantly decreased ($p < .05$) when comparing monthly use to daily reading of the following items: directions or instructions ($M = 261$ with monthly use and $M = 251$ with weekly use), newspapers or magazines ($M = 264$ and $M = 258$), professional journals ($M = 265$ and $M = 258$), books ($M = 262$ and $M = 253$), manuals or reference journals ($M = 262$ and $M = 251$), financial statements ($M = 265$ and $M = 257$), and diagrams, maps or schematics ($M = 267$ and $M = 259$),

Technical/computer skill use at work. Substantial variability in the frequency of skill use was reported on the items used to measure technical/computer skill use at work (see Table 4.13). For example, the majority of both groups indicated daily use of the Internet to collect work-related information (51% to 61%), whereas they never used a computer programming language at work (78% to 87%). In general, a larger percentage of the most proficient group demonstrated more frequent use of technical/computer skills at work.

Learning at work. Items comprising the Learning at Work factor demonstrated the least amount of group differences in frequency of use. In fact, the frequency of usage between the higher and lower proficiency levels was within 8% for every frequency category (see Table 4.14). Less than 10% of individuals from either group indicated that they never learned things from co-workers/supervisors, never learned by doing tasks at work, and that their job never required them to keep up-to-date on new products or services. For the less numerically proficient group, the mean scores were significantly lower for those who reported the use of the skill on a daily basis compared to those who used the skill monthly.

Job culture/problem solving at work. The factor measuring the culture at work includes planning and problem solving at work (see Table 4.15). The highly numerate group was significantly ($p < .001$) more likely to plan their own activities on a daily basis (63%, $SE = 2.8$) or to organize their own time on a daily basis (82%, $SE = 2.4$) compared to the lower numeracy group (48%, $SE = 0.9$; 65%, $SE = 0.9$). Although both groups appeared similar on their frequency of solving simple problems, a larger percentage of the highly numerate group solved complex problems more than once a week (57%) compared to the lower numeracy group (43%).

Intrapersonal Characteristics

Gender. Males outperformed females in numeracy proficiency (see Table 4.16). Significantly more males (66%, $SE = 2.5$) comprised the highly numerate group, and significantly more females (53%, $SE = 0.3$) comprised the lower numeracy ability group ($p < .001$ for both). The average numeracy score for males in the low numeracy group, however, was significantly larger ($M = 251$, $SE = 1.2$; $p < .001$) compared to females (M = 243, $SE = 1.3$).

Table 4.11

Numeracy at Work Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				> 1x week < every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Calculating costs or budgets (G Q03B)																				
Bottom 90%	244	(1.5)	44	(0.8)	263	(2.6)	9	(0.5)	264	(3.6)	7	(0.5)	262	(2.9)	10	(0.7)	253	(1.7)	30	(0.8)
Top 10%	347	(2.0)	31	(2.8)	347	(2.4)	16	(2.0)	348	(2.8)	13	(2.1)	350	(2.6)	18	(2.2)	346	(2.0)	22	(2.8)
Use or calculate fractions or %s (G_Q03C)																				
Bottom 90%	235	(1.7)	36	(0.7)	260	(2.9)	9	(0.5)	270	(2.4)	7	(0.5)	265	(2.5)	13	(0.7)	259	(1.4)	35	(0.9)
Top 10%	343	(2.1)	14	(1.9)	349	(3.7)	11	(1.8)	349	(2.6)	14	(2.4)	347	(1.9)	20	(2.5)	348	(1.7)	41	(3.2)
Use a calculator (G_Q03D)																				
Bottom 90%	233	(1.8)	29	(0.6)	258	(2.5)	7	(0.5)	269	(2.7)	8	(0.5)	265	(2.0)	16	(0.7)	257	(1.5)	40	(0.9)
Top 10%	345	(2.6)	11	(1.7)	‡	†	8	(1.7)	348	(2.9)	15	(2.0)	348	(2.2)	26	(2.3)	347	(1.7)	39	(3.0)
Prepare charts graphs or tables (G Q03F)																				
Bottom 90%	242	(1.5)	57	(0.8)	269	(2.0)	13	(0.6)	269	(2.3)	10	(0.6)	266	(2.6)	11	(0.6)	256	(2.9)	9	(0.4)
Top 10%	345	(1.8)	28	(2.5)	347	(3.0)	21	(1.9)	349	(2.4)	20	(2.2)	349	(2.2)	20	(2.2)	349	(3.6)	12	(1.7)
Use simple algebra or formulas (G_Q03G)																				
Bottom 90%	240	(1.3)	56	(0.7)	267	(2.7)	10	(0.5)	274	(2.7)	7	(0.5)	273	(2.1)	9	(0.6)	262	(2.1)	17	(0.7)
Top 10%	344	(1.8)	24	(2.3)	344	(2.7)	13	(2.0)	350	(2.5)	16	(2.1)	348	(2.2)	22	(2.5)	350	(2.6)	25	(2.5)
Use advanced math or statistics (G_Q03H)																				
Bottom 90%	249	(1.2)	84	(0.7)	272	(3.5)	7	(0.4)	274	(4.0)	3	(0.3)	270	(4.6)	3	(0.3)	258	(5.4)	3	(0.3)
Top 10%	346	(1.1)	61	(2.8)	349	(2.5)	16	(2.0)	‡	†	10	(1.8)	‡	†	8	(1.5)	‡	†	5	(1.2)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.12

Reading at Work Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				>1x week < every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Read directions or instructions (G_Q01A)																				
Bottom 90%	233	(2.8)	12	(0.5)	257	(2.8)	10	(0.5)	261	(3.0)	9	(0.4)	260	(1.8)	18	(0.7)	251	(1.4)	51	(0.8)
Top 10%	‡	†	5	(1.2)	346	(2.7)	13	(1.8)	351	(3.4)	14	(2.0)	349	(2.5)	26	(2.6)	346	(1.4)	41	(3.0)
Read directions or instructions (G Q01A)																				
Bottom 90%	227	(2.6)	21	(0.8)	252	(3.2)	5	(0.4)	255	(3.2)	5	(0.4)	250	(2.3)	11	(0.5)	261	(1.2)	57	(0.8)
Top 10%	‡	†	6	(1.4)	‡	†	4	(1.2)	‡	†	4	(1.2)	‡	†	8	(1.4)	348	(1.1)	78	(2.3)
Read newspapers or magazines (G Q01C)																				
Bottom 90%	236	(1.7)	33	(0.7)	255	(2.8)	11	(0.5)	264	(2.5)	11	(0.7)	262	(1.9)	22	(0.7)	258	(1.6)	22	(0.7)
Top 10%	344	(2.1)	15	(2.1)	350	(4.4)	11	(2.1)	348	(2.4)	16	(2.2)	348	(1.8)	28	(2.8)	347	(2.2)	30	(3.3)
Read professional journals (G Q01D)																				
Bottom 90%	239	(1.5)	45	(0.9)	259	(2.2)	15	(0.6)	265	(2.5)	13	(0.6)	266	(2.0)	17	(0.7)	258	(2.4)	10	(0.6)
Top 10%	345	(1.9)	23	(2.6)	349	(3.1)	17	(2.2)	349	(2.2)	22	(2.4)	348	(2.1)	30	(3.2)	‡	†	9	(1.8)
Read books (G_Q01E)																				
Bottom 90%	247	(1.3)	57	(0.8)	265	(2.4)	17	(0.6)	261	(3.5)	9	(0.5)	252	(3.3)	8	(0.4)	253	(2.8)	10	(0.5)
Top 10%	346	(1.5)	39	(2.5)	350	(1.7)	33	(2.4)	348	(3.6)	14	(1.7)	‡	†	7	(1.6)	‡	†	7	(1.3)
Read manuals or reference materials (G_Q01F)																				
Bottom 90%	234	(2.0)	20	(0.6)	258	(2.4)	21	(0.7)	262	(2.2)	17	(0.7)	257	(2.0)	20	(0.7)	251	(1.7)	22	(0.8)
Top 10%	344	(3.1)	11	(1.5)	348	(1.8)	27	(3.0)	347	(2.1)	24	(2.8)	350	(2.6)	21	(2.0)	346	(2.1)	18	(2.3)
Read financial statements (G_Q01G)																				
Bottom 90%	243	(1.4)	49	(1.0)	264	(3.3)	8	(0.5)	265	(2.9)	9	(0.5)	260	(2.1)	13	(0.6)	257	(1.8)	21	(0.7)
Top 10%	347	(1.6)	35	(2.9)	348	(2.5)	16	(1.7)	347	(3.1)	14	(2.1)	349	(2.4)	18	(2.4)	346	(2.4)	17	(2.3)
Read diagrams maps or schematics (G_Q01H)																				
Bottom 90%	239	(1.9)	44	(0.6)	263	(2.0)	15	(0.6)	267	(2.6)	9	(0.6)	264	(2.3)	12	(0.6)	259	(1.6)	19	(0.6)
Top 10%	343	(1.7)	23	(2.3)	349	(2.6)	19	(2.4)	350	(2.8)	21	(2.5)	348	(2.2)	17	(2.1)	348	(2.4)	20	(2.3)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.13

Technical/Computer Skill Use at Work Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				> 1x week < every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Internet to collect info (G_Q05C)																				
Bottom 90%	245	(2.4)	17	(0.8)	263	(4.2)	7	(0.6)	260	(3.4)	8	(0.5)	266	(2.4)	17	(0.7)	265	(1.5)	51	(1.1)
Top 10%	‡	†	5	(1.3)	‡	†	7	(1.9)	‡	†	7	(1.5)	348	(2.3)	20	(2.4)	348	(1.6)	61	(3.1)
Internet to conduct transactions (G_Q05D)																				
Bottom 90%	257	(1.5)	53	(1.3)	269	(3.8)	9	(0.6)	269	(3.0)	8	(0.5)	272	(2.6)	11	(0.7)	261	(2.3)	19	(0.9)
Top 10%	347	(1.7)	42	(2.7)	347	(2.6)	15	(2.3)	350	(2.7)	13	(1.8)	349	(2.9)	14	(2.1)	347	(3.2)	16	(2.0)
Use spreadsheets (G_Q05E)																				
Bottom 90%	250	(1.7)	37	(1.1)	265	(2.7)	9	(0.7)	269	(3.3)	9	(0.6)	270	(2.6)	14	(0.8)	268	(1.7)	30	(1.0)
Top 10%	345	(2.2)	18	(2.2)	‡	†	9	(1.5)	350	(3.9)	13	(1.7)	348	(2.0)	22	(2.6)	348	(2.0)	39	(2.8)
Use programming language (G_Q05G)																				
Bottom 90%	261	(1.1)	87	(0.8)	264	(4.8)	4	(0.5)	273	(5.4)	2	(0.3)	261	(7.3)	3	(0.3)	258	(5.3)	4	(0.5)
Top 10%	347	(1.1)	78	(2.2)	‡	†	7	(1.4)	‡	†	4	(1.0)	‡	†	4	(1.4)	‡	†	7	(1.6)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.14

Learning at Work Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				> 1x week < every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Learning from co-workers/supervisors (D_Q13A)																				
Bottom 90%	240	(3.8)	8	(0.6)	252	(2.8)	19	(0.7)	264	(1.9)	21	(0.8)	257	(2.1)	26	(0.7)	244	(2.2)	27	(0.8)
Top 10%	‡	†	4	(1.7)	348	(2.7)	16	(2.3)	350	(2.4)	29	(2.6)	347	(2.2)	30	(2.8)	349	(3.2)	21	(2.1)
Keeping up to date (D_Q13C)																				
Bottom 90%	232	(2.9)	10	(0.6)	256	(2.4)	20	(0.6)	265	(2.1)	17	(0.8)	259	(2.0)	17	(0.7)	249	(1.8)	36	(1.0)
Top 10%	‡	†	3	(1.1)	347	(2.4)	24	(2.2)	348	(2.1)	25	(2.7)	348	(2.2)	21	(2.3)	347	(2.8)	27	(2.8)

Table 4.15

Job Culture/Problem Solving Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				>1x week <every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Simple problems (F_Q05A)																				
Bottom 90%	213	(3.9)	5	(0.4)	231	(4.7)	8	(0.7)	249	(3.0)	8	(0.5)	255	(2.1)	23	(0.7)	258	(1.3)	55	(1.0)
Top 10%	‡	†	2	(0.7)	‡	†	5	(1.4)	‡	†	7	(1.7)	349	(2.1)	24	(2.1)	347	(1.2)	62	(2.9)
Complex problems (F_Q05B)																				
Bottom 90%	236	(2.0)	18	(0.7)	247	(2.2)	19	(0.7)	258	(2.1)	19	(0.5)	261	(1.8)	29	(0.7)	253	(2.2)	14	(0.5)
Top 10%	‡	†	8	(1.5)	346	(3.3)	15	(1.9)	346	(1.9)	20	(2.0)	349	(1.9)	41	(2.7)	349	(2.8)	16	(2.0)
Planning own activities (F_Q03A)																				
Bottom 90%	237	(2.2)	26	(0.7)	253	(3.5)	8	(0.5)	250	(3.4)	6	(0.5)	255	(2.7)	12	(0.6)	259	(1.5)	48	(0.9)
Top 10%	343	(2.9)	10	(1.8)	‡	†	6	(1.3)	‡	†	6	(1.3)	348	(2.5)	15	(1.8)	348	(1.3)	63	(2.8)
Planning others activities (F_Q03B)																				
Bottom 90%	242	(1.7)	43	(0.8)	261	(2.4)	10	(0.6)	266	(2.8)	8	(0.4)	263	(2.2)	13	(0.7)	256	(2.0)	26	(0.9)
Top 10%	347	(2.4)	27	(2.6)	348	(3.2)	12	(2.0)	347	(2.9)	14	(1.9)	349	(2.2)	21	(2.1)	347	(2.0)	27	(2.5)
Organizing own time (F_Q03C)																				
Bottom 90%	232	(2.4)	18	(0.7)	249	(4.2)	4	(0.4)	248	(3.6)	4	(0.4)	253	(3.1)	8	(0.4)	258	(1.3)	65	(0.9)
Top 10%	‡	†	5	(1.2)	‡	†	2	(0.8)	‡	†	3	(1.1)	‡	†	7	(1.6)	348	(1.1)	82	(2.4)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.16

Gender (GENDER_R) by Numeracy Proficiency Level

Numeracy Competency	Male				Female			
	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	251	(1.2)	47	(0.3)	243	(1.3)	53	(0.3)
Top 10%	348	(1.2)	66	(2.5)	345	(1.4)	34	(2.5)

Native language. The PIAAC has a derived variable for native language indicating if the test language is the same language spoken most often at home. The percentage of individuals whose native language was the same as the test language was significantly higher ($p < .001$) for the top 10% numeracy group (95%, SE = 1.2) compared to the group with less numeracy skills (86%, SE = 0.9, see Table 4.17). Although the average numeracy score for non-native speakers that scored in the top 10% is not provided, the average score of the less numerate adults was significantly less ($p < .001$) for non-native speakers (M = 214; SE = 4.2) compared to native speakers (M = 251 SE = 1.1).

Table 4.17

Test is in Native Language (NATIVELANG) by Numeracy Proficiency Level

Numeracy Competency	Yes				No			
	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	251[1]	(1.1)	86[1]	(0.9)	214[1]	(4.2)	14[1]	(0.9)
Top 10%	347[1]	(1.1)	95[1]	(1.2)	‡	†	5[1]	(1.2)

Note. † Not applicable. ‡ Reporting standards not met. [1]The item response rate is below 85 percent. Missing data have not been explicitly accounted for.

Race/ethnicity. White individuals were disproportionately represented in the top 10% of numerate individuals and they earned higher mean scores. In fact, the group of most numerate adults was comprised of 85% White, 4% Hispanic, 2% Black, and 8% other races (see Table 4.18). As a point of reference, the percentage of all PIAAC adults by race was 65% White, 15% Hispanic, 13% Black, and 7% other races. An individual of Hispanic or Black ethnicity was significantly more likely ($p < .001$) to be in the lower numeracy group, and an individual with a White ethnicity was significantly ($p < .001$) more likely to be in the highest numeracy group. Furthermore, the White group had the highest mean numeracy scores ($M = 273$; $SE = 1.3$) compared to the other groups: Hispanic ($M = 222$; $SE = 3.5$), Black ($M = 217$; $SE = 2.7$), or other ($M = 260$; $SE = 2.9$).

Age. Whereas the youngest (16-24) and the oldest (55-65) highly numerate adults were underrepresented compared to adults aged 25-54, the highly numerate adults' mean proficiency score remained fairly consistent between the age bands (see Table 4.19). For example, the percentage of highly numerate individuals within each age band rose sharply from 14% to 26% at age 25-34 and then gradually decreased to 15% for individuals aged 55-65. In contrast, within the lower numeracy group, the age bands were evenly distributed with approximately 20% in each of five 10-year age bands. Average numeracy also peaked between ages 25 to 34 for both groups ($M = 350$, $SE = 1.8$; $M = 255$, $SE = 1.5$), but the less proficient group generally had larger declines in their numeracy proficiency scores in the older age bands. For example, the average score difference between the peak and pre-retirement age was only 3 points for the most numerate group compared to 11 points for the less numerate group.

Health. Individuals with the top 10% of numeracy skills were more likely to report a more favorable health status, with 75% rating their health as very good or excellent (see Table 4.20). In contrast, 54% of individuals with less numeracy skills indicated very good to excellent health. Only 5% of highly numerate individuals described their health as fair or poor contrasted with 16% of those with less numeracy skills. For the bottom 90% group, the average score of those who reported very good or excellent health was significantly higher ($M = 257$; $p < .001$) than those who reported good ($M = 243$), fair ($M = 222$), or poor health ($M = 219$). Almost all of the highest numeracy group (94%; $SE = 1.4$) reported medical insurance coverage compared to only 78% ($SE = 0.8$) of the other group (see Table 4.21).

Learning disability, vision or hearing difficulty. A significantly smaller percentage ($p < .001$) of the highly numerate group reported a learning disability or difficulty seeing print compared to the less able group (see Table 4.22). For example, only 4% ($SE = 1.0$) of the highly numerate group indicated the presence of a learning disability whereas 8% ($SE = 0.5$) of the less proficient group had a learning disability. In the bottom 90% numerate skills group, the average score for those with a learning disability ($M = 226$) was significantly lower than for those who did not indicate the presence of a learning disability ($M = 249$).

The groups were distributed similarly for the item, "Do you have any difficulty hearing what is said in a normal conversation with another person even when using a hearing aid if you usually wear one?" (National Center for Education Statistics, 2012, n.p.). Another item queried, "Do you have any difficulty seeing words and letters in ordinary newspaper print even when wearing glasses or contact lenses if you usually wear them"(National Center for Education Statistics, 2012, n.p.). Only 5% ($SE = 1.0$) of individuals with the top 10% of numeracy skills indicated difficulty seeing print, whereas

Table 4.18

Race/Ethnicity (RACETHN4CAT) Overall and by Numeracy Proficiency Level

Numeracy Competency	Hispanic				White				Black				Other race			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	218	(3.5)	16	(0.4)	261	(1.1)	63	(0.8)	215	(2.8)	14	(0.2)	249	(2.7)	7	(0.7)
Top 10%	‡	†	4	(1.2)	348	(1.0)	85	(2.1)	‡	†	2	(0.6)	347	(3.0)	8	(1.5)
All adults (16-65)	222	(3.5)	15	(0.4)	273	(1.3)	65	(0.8)	217	(2.7)	13	(0.1)	260	(2.9)	7	(0.7)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.19

Age Groups in 10-year Intervals (AGEG10LFS) by Numeracy Proficiency Level

Numeracy Competency	24 or less				25-34				35-44				45-54				55-65			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	246	(1.7)	19	(0.3)	255	(1.8)	20	(0.4)	249	(1.5)	19	(0.4)	242	(2.0)	21	(0.4)	244	(1.7)	21	(0.3)
Top 10%	346	(2.8)	14	(2.0)	350	(1.8)	26	(2.2)	347	(2.4)	24	(2.0)	345	(2.2)	21	(2.3)	347	(2.3)	15	(2.0)

Table 4.20

Self-Described Health Status (I_Q08) by Numeracy Proficiency Level

Numeracy Competency	Excellent				Very good				Good				Fair				Poor			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	257	(1.6)	22	(0.8)	257	(1.3)	32	(0.7)	243	(2.3)	29	(0.8)	222	(2.6)	12	(0.5)	219	(4.0)	4	(0.2)
Top 10%	348	(2.1)	34	(2.8)	347	(1.7)	41	(3.0)	348	(2.5)	19	(2.4)	‡	†	4	(1.1)	‡	†	1	(0.4)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.21

Health Insurance Coverage (I_Q10BUSX1) by Numeracy Proficiency Level

Numeracy Competency	Yes				No			
	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	252	(1.1)	78	(0.8)	228	(2.2)	22	(0.8)
Top 10%	348	(1.0)	94	(1.4)	‡	†	6	(1.4)

Note. † Not applicable. ‡ Reporting standards not met.

12% (*SE* = 0.5) of the less numerate adults indicated difficultly seeing print (see Table 4.22). In the latter group, the average score for those reported difficulty seeing print (*M* = 223, *SE* = 2.8) were significantly lower ($p < .001$) than those who did not have problems seeing print (*M* = 250; *SE* = 1.0).

Table 4.22

Disability/Health Difficulty by Numeracy Proficiency Level

Numeracy	Yes				No			
Competency	Avg.	SE	%	SE	Avg.	SE	%	SE
Learning Disabled (I_Q08USX3)								
Bottom 90%	226	(3.1)	8	(0.5)	249	(1.1)	92	(0.5)
Top 10%	‡	†	4	(1.0)	347	(0.9)	96	(1.0)
Difficulty hearing conversation (I_Q08USX2)								
Bottom 90%	244	(2.6)	9	(0.5)	247	(1.1)	91	(0.5)
Top 10%	‡	†	8	(1.3)	347	(1.0)	92	(1.3)
Difficulty seeing print (I_Q08USX1)								
Bottom 90%	223	(2.8)	12	(0.5)	250	(1.0)	88	(0.5)
Top 10%	‡	†	5	(1.0)	347	(0.9)	95	(1.0)

Note. † Not applicable. ‡ Reporting standards not met.

Persistence. To investigate a facet of persistence, the PIAAC item asking if participants discontinued studying for a formal degree program before completion of the degree was selected. Approximately 30% of both groups indicated that they had left a degree program before completion (28%, *SE* = 3.4; vs. 32%, *SE* = .09) (see Table 4.23). Furthermore, there was not a statistically significant difference between the mean numeracy scores between those who persisted and those who did not.

Table 4.23

Persistence/Uncompleted Qualification (B_Q03A) by Numeracy Proficiency Level

Numeracy	Yes				No			
Competency	Avg.	SE	%	SE	Avg.	SE	%	SE
Bottom 90%	248	(1.7)	32	(0.9)	245	(1.3)	68	(0.9)
Top 10%	347	(2.4)	28	(3.4)	348	(1.2)	72	(3.4)

Numeracy at home. A greater percentage of the highly proficient group reported more frequent use of some numeracy skills at home compared to those at lower proficiency levels (see Table 4.24). The most proficient group compared to the less numerate group used the following skills more than once a week: fractions/percentages (57% vs. 37%), calculator use (56% vs. 48%), and simple algebra or formulas (32% vs. 19%). The skill used least frequently was advanced math and statistics, with 61% (*SE* = 2.7) of the most proficient group and 83% (*SE* = 0.6) of the lower proficiency group indicating they never used those skills in everyday life. Only 20% (*SE* = 2.1) of individuals in the highest numeracy group reported no use of simple algebra or the formulas in their daily life, but 57% (*SE* = 0.8) of the lower numeracy group never used these skills outside of work. It appeared those who indicated at least monthly use of algebra/formulas generally had the highest mean scores compared to other skill usages.

Technical/computer skill use at home. Some differences between the groups were observed in the use of technology/computer skills in everyday life (see Table 4.25). A higher percentage of the top numerate group used the following skills more than once a week compared to the less numerate group: internet to conduct transactions (60% vs. 46%) and spreadsheets (21% vs. 11%). Almost all participants indicated using the Internet to understand issues at least once a month, whereas the use of computer

Table 4.24

Numeracy at Home Factor: Item by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				>1x week < every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Calculating costs or budgets (H_Q03B)																				
Bottom 90%	225	(2.9)	13	(0.6)	250	(2.3)	12	(0.5)	252	(2.3)	18	(0.7)	253	(1.5)	34	(0.7)	245	(1.7)	24	(0.7)
Top 10%	‡	†	6	(1.3)	347	(2.8)	15	(1.9)	348	(2.3)	20	(2.5)	347	(1.5)	40	(2.7)	347	(2.4)	18	(2.1)
Use or calculate fractions or percentages (H_Q03C)																				
Bottom 90%	222	(1.9)	28	(0.7)	251	(1.7)	18	(0.6)	262	(1.7)	16	(0.6)	261	(1.5)	23	(0.7)	253	(2.0)	15	(0.5)
Top 10%	‡	†	5	(1.4)	344	(2.6)	13	(1.8)	348	(1.9)	25	(2.3)	348	(1.4)	39	(2.9)	347	(2.3)	18	(2.1)
Use a calculator (H_Q03D)																				
Bottom 90%	216	(2.4)	16	(0.5)	247	(2.1)	15	(0.4)	256	(1.9)	21	(0.7)	257	(1.6)	32	(0.7)	246	(1.9)	16	(0.6)
Top 10%	‡	†	3	(0.7)	347	(3.5)	14	(1.8)	348	(1.9)	27	(2.2)	347	(1.4)	44	(2.5)	345	(3.7)	12	(1.9)
Prepare charts graphs or tables (H_Q03F)																				
Bottom 90%	241	(1.1)	72	(0.6)	268	(1.9)	15	(0.5)	261	(2.8)	7	(0.4)	254	(3.7)	5	(0.3)	240	(6.8)	2	(0.2)
Top 10%	345	(1.9)	44	(2.6)	351	(2.0)	31	(2.2)	348	(2.2)	16	(1.8)	‡	†	7	(1.2)	‡	†	1	(0.6)
Use simple algebra or formulas (H Q03G)																				
Bottom 90%	234	(1.3)	57	(0.8)	267	(1.9)	15	(0.5)	268	(2.3)	9	(0.4)	262	(2.5)	10	(0.5)	256	(2.4)	9	(0.4)
Top 10%	342	(1.8)	20	(2.1)	347	(2.3)	28	(2.4)	350	(2.5)	20	(2.2)	348	(2.0)	20	(2.0)	349	(3.1)	12	(1.7)
Use advanced math or statistics (H_Q03H)																				
Bottom 90%	244	(1.1)	83	(0.6)	270	(2.6)	8	(0.4)	264	(3.9)	3	(0.2)	251	(3.6)	3	(0.3)	257	(3.8)	3	(0.2)
Top 10%	346	(1.3)	61	(2.7)	350	(2.4)	20	(2.4)	352	(4.2)	10	(1.5)	‡	†	5	(1.2)	‡	†	3	(0.9)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.25

Technical/Computer Skill Use at Home Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				>1x week < every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Internet to understand issues (H_Q05C)																				
Bottom 90%	225	(3.9)	5	(0.4)	246	(2.7)	9	(0.5)	259	(2.6)	14	(0.6)	262	(1.7)	30	(0.8)	258	(1.2)	42	(1.0)
Top 10%	‡	†	1	(0.4)	‡	†	4	(1.2)	346	(2.7)	13	(1.7)	348	(2.0)	36	(2.4)	348	(1.5)	46	(2.4)
Internet to conduct transactions (H Q05D)																				
Bottom 90%	227	(2.3)	16	(0.6)	254	(2.4)	16	(0.6)	264	(1.8)	21	(0.6)	269	(1.3)	30	(1.0)	255	(2.1)	16	(0.7)
Top 10%	‡	†	2	(0.8)	‡	†	8	(1.6)	348	(1.7)	29	(2.8)	349	(1.5)	47	(2.8)	345	(2.5)	13	(1.8)
Spreadsheets (H Q05E)																				
Bottom 90%	246	(1.2)	55	(0.8)	269	(1.7)	22	(0.7)	273	(2.3)	12	(0.5)	266	(2.9)	8	(0.4)	253	(4.4)	3	(0.3)
Top 10%	343	(2.1)	19	(2.3)	348	(1.9)	34	(3.0)	350	(2.0)	26	(2.6)	347	(2.8)	17	(1.8)	‡	†	4	(1.1)
Programming language (H_Q05G)																				
Bottom 90%	256	(0.9)	91	(0.5)	266	(3.7)	4	(0.3)	262	(5.9)	2	(0.2)	253	(6.8)	2	(0.2)	252	####	1	(0.2)
Top 10%	347	(1.1)	81	(2.2)	350	(3.2)	11	(1.7)	‡	†	4	(1.0)	‡	†	3	(0.9)	‡	†	1	(0.6)

Note. † Not applicable. ‡ Reporting standards not met.

programming language in everyday life was rare for both groups. For example, 19% from the higher numeracy skills group indicated at least some use of these skills in daily life compared to 9% of the lower numeracy group. Individuals who never used the Internet for understanding issues or conducting transactions in their everyday life had the lowest numeracy scores (*M* = 225 and *M* =227 respectively).

Learning motivation. Individuals in the top 10% of numeracy were significantly more likely to engage in training and education (see Table 4.26). For example, 77% (*SE* = 2.3) of the top numerate group enrolled in courses outside of their program of studies compared to 55% (*SE* = 1.0) of their peers. Additionally, a significantly higher percentage of the highly numerate group participated in open/distance education, on-the-job training, seminars or workshops, private lessons, and job-related training. The only nonsignificant difference between the groups was participation in job-related training. Interestingly, within the lower numerate group, participation in any of the aforementioned learning activities was associated with higher average numeracy scores.

Learning approach. The vast majority of individuals from both numeracy groups reported the use of all the various learning strategies (see Table 4.27). Over half the individuals from both groups utilized each strategy to a high extent or to a very high extent. However, differences of 12% or greater were reported for the following items: relate to real life (69% vs. 44%), attribute to something new (83% vs. 66%), and like learning new things (92% vs. 80%). Lower mean scores were associated with participants who indicated they did not utilize the strategies at all (*M* = 201 to 211) or only to a very little extent (M = 206 to 221). Those who reported no use of strategies had the lowest mean scores of any environmental or intrapersonal item examined thus far.

Table 4.26

Learning Motivation Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Yes				No			
	Avg.	SE	%	SE	Avg.	SE	%	SE
Courses outside of program of studies (B Q12A T)								
Bottom 90%	259	(1.1)	55	(1.0)	233	(1.4)	45	(1.0)
Top 10%	348	(1.0)	77	(2.3)	345	(1.9)	23	(2.3)
Open or distance education (B Q12A)								
Bottom 90%	262	(1.9)	16	(0.6)	245	(1.1)	84	(0.6)
Top 10%	346	(2.4)	24	(2.2)	348	(1.0)	76	(2.2)
On the job training (B Q12C)								
Bottom 90%	259	(1.2)	39	(0.9)	240	(1.3)	61	(0.9)
Top 10%	348	(1.3)	53	(2.6)	346	(1.6)	47	(2.6)
Seminars or workshops (B Q12E)								
Bottom 90%	264	(1.3)	29	(0.7)	241	(1.2)	71	(0.7)
Top 10%	348	(1.4)	46	(2.4)	346	(1.2)	54	(2.4)
Private lessons (B Q12G)								
Bottom 90%	265	(3.0)	8	(0.6)	246	(1.1)	92	(0.6)
Top 10%	349	(2.7)	16	(2.0)	347	(0.9)	84	(2.0)
Job related (B_Q14A)								
Bottom 90%	267	(1.8)	68	(1.7)	262	(2.8)	32	(1.7)
Top 10%	349	(1.9)	74	(3.4)	346	(2.6)	26	(3.4)

Reading at home. The majority of the high numeracy group integrated reading activities more than once a week except for reading professional journals, reading manuals or reference materials, and reading maps or schematics (see Table 4.28). A difference of over 10% between the high and low numerate groups was reported for reading the following activities more than once a week: letters, memos, or mail (95% vs. 81%); newspapers or magazines (86% vs. 74%); diagrams, maps or schematics (29% vs. 17%); and books (56% vs. 45%). Individuals who indicated they never read had the

Table 4.27

Learning Approach Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Not at all				Very little				To some extent				To a high extent				To a very high extent			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Relate to real life (I_Q04B)																				
Bottom 90%	202	(4.4)	3	(0.2)	214	(3.1)	10	(0.5)	245	(1.3)	43	(0.8)	262	(1.4)	28	(0.8)	256	(2.0)	16	(0.6)
Top 10%	‡	†	‡	†	‡	†	2	(0.6)	344	(1.5)	29	(2.2)	349	(1.5)	45	(2.6)	348	(2.1)	24	(2.3)
Like learning new things (I Q04D)																				
Bottom 90%	‡	†	1	(0.1)	209	(6.9)	2	(0.2)	235	(2.1)	18	(0.6)	252	(1.4)	35	(0.7)	250	(1.2)	45	(0.8)
Top 10%	‡	†	‡	†	‡	†	‡	†	‡	†	8	(1.4)	346	(1.4)	38	(2.6)	348	(1.5)	54	(2.6)
Attribute something new (I_Q04H)																				
Bottom 90%	201	(7.2)	1	(0.2)	206	(4.1)	4	(0.3)	240	(1.8)	28	(0.7)	256	(1.2)	39	(0.8)	250	(1.5)	27	(0.8)
Top 10%	‡	†	‡	†	‡	†	#	†	345	(2.5)	17	(1.9)	346	(1.3)	46	(2.6)	349	(1.8)	37	(2.6)
Difficult things (I_Q04J)																				
Bottom 90%	204	(7.1)	2	(0.2)	214	(3.7)	5	(0.3)	245	(2.1)	25	(0.8)	255	(1.6)	35	(0.7)	247	(1.2)	34	(0.8)
Top 10%	‡	†	‡	†	‡	†	1	(0.5)	345	(2.3)	19	(2.4)	346	(1.2)	41	(2.3)	350	(1.7)	39	(2.6)
Ideas fit together (I Q04L)																				
Bottom 90%	211	(6.0)	2	(0.2)	221	(4.2)	6	(0.3)	246	(1.5)	31	(0.7)	253	(1.6)	35	(0.7)	249	(1.5)	26	(0.7)
Top 10%	‡	†	‡	†	‡	†	2	(0.8)	345	(2.1)	25	(2.7)	346	(1.4)	42	(2.7)	350	(2.1)	30	(2.6)
Look for additional info (I_Q04M)																				
Bottom 90%	‡	†	1	(0.1)	209	(5.5)	3	(0.2)	243	(2.3)	18	(0.6)	251	(1.6)	38	(0.8)	249	(1.2)	41	(0.9)
Top 10%	‡	†	‡	†	‡	†	‡	†	348	(3.5)	15	(1.9)	347	(1.6)	43	(2.7)	347	(1.5)	42	(2.7)

Note. † Not applicable. ‡ Reporting standards not met.

Table 4.28

Reading at Home Factor: Item Responses by Numeracy Proficiency Level

Numeracy Competency	Never				< 1x month				monthly to weekly				> 1x week < every day				Every day			
	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE	Avg.	SE	%	SE
Read directions or instructions (H Q01A)																				
Bottom 90%	217	(3.8)	10	(0.5)	255	(2.1)	15	(0.7)	256	(2.1)	15	(0.7)	255	(1.2)	27	(0.6)	243	(1.4)	33	(0.8)
Top 10%	‡	†	2	(0.9)	350	(3.0)	22	(2.5)	348	(2.0)	21	(2.3)	348	(1.9)	35	(2.8)	344	(2.2)	19	(2.1)
Read letters, memos, or mail (H Q01B)																				
Bottom 90%	202	(3.7)	8	(0.4)	224	(3.7)	5	(0.3)	236	(3.1)	6	(0.4)	248	(2.0)	18	(0.6)	255	(0.9)	63	(0.9)
Top 10%	‡	†	‡	†	‡	†	1	(0.4)	‡	†	3	(1.1)	347	(2.9)	14	(1.9)	347	(1.0)	81	(2.1)
Read newspapers or magazines (H Q01C)																				
Bottom 90%	207	(3.5)	9	(0.5)	235	(3.7)	7	(0.4)	247	(2.6)	10	(0.5)	249	(1.5)	29	(0.8)	255	(1.3)	45	(0.9)
Top 10%	‡	†	1	(0.8)	‡	†	4	(1.1)	346	(2.8)	9	(1.7)	347	(2.0)	30	(2.3)	348	(1.2)	56	(2.9)
Read professional journals (H Q01D)																				
Bottom 90%	229	(1.6)	38	(0.8)	262	(1.8)	20	(0.6)	261	(1.9)	16	(0.6)	257	(1.7)	17	(0.6)	246	(2.6)	9	(0.4)
Top 10%	346	(2.8)	15	(1.7)	350	(2.0)	28	(2.6)	347	(2.0)	26	(2.3)	346	(1.8)	23	(2.9)	‡	†	7	(1.6)
Read books (H_Q01E)																				
Bottom 90%	226	(2.0)	21	(0.7)	250	(1.8)	21	(0.6)	252	(2.2)	13	(0.5)	255	(1.9)	19	(0.6)	254	(1.5)	26	(0.7)
Top 10%	‡	†	7	(1.3)	346	(2.1)	22	(2.4)	347	(2.8)	15	(2.0)	350	(2.2)	27	(2.3)	347	(1.7)	29	(2.2)
Read manuals or reference materials (H_Q01F)																				
Bottom 90%	227	(2.1)	27	(0.7)	257	(1.4)	28	(0.8)	258	(1.8)	19	(0.7)	253	(1.9)	17	(0.7)	242	(2.8)	9	(0.5)
Top 10%	346	(3.7)	11	(1.7)	347	(1.7)	37	(2.9)	348	(1.7)	28	(2.6)	348	(2.2)	19	(2.1)	‡	†	6	(1.4)
Read financial statements (H_Q01G)																				
Bottom 90%	220	(3.3)	11	(0.5)	242	(2.6)	9	(0.4)	251	(2.0)	20	(0.6)	258	(1.5)	34	(0.6)	243	(1.4)	26	(0.7)
Top 10%	‡	†	2	(0.9)	‡	†	8	(1.6)	348	(2.5)	24	(2.3)	348	(1.4)	50	(2.8)	344	(2.6)	15	(1.9)
Read diagrams maps or schematics (H_Q01H)																				
Bottom 90%	227	(1.5)	40	(0.9)	261	(1.2)	27	(0.7)	263	(2.0)	15	(0.5)	260	(2.1)	12	(0.5)	251	(3.3)	5	(0.3)
Top 10%	342	(2.6)	9	(1.6)	347	(2.2)	34	(2.6)	349	(2.0)	29	(2.7)	349	(2.1)	23	(2.6)	‡	†	6	(1.1)

Note. † Not applicable. ‡ Reporting standards not met.

lowest average numeracy scores within their respective groups and were similar to the mean scores for those who indicated never using learning strategies.

Confirmatory Factor Analysis

To maximize the potential of the model fitting the data, the CFA was conducted step by step beginning with each of the single factors (e.g., Numeracy at Work, Learning Approach, Numeracy at Home, etc.) before running a CFA on the second-order factors (e.g., Intrapersonal and Environmental). Appendix A provides a correlation table for each first-order factor and path values for each CFA before and after modifications. Additionally, a large correlation table for all item-level indicators is available at https://goo.gl/gdshXc. To improve model fit, modification indices were examined for areas of strain. When supported by theory, indicators within factors were correlated, and some indicators were dropped to maximize CFA model fit.

After fitting individual first-order factors, CFAs were conducted for the Intrapersonal second-order factor and the Environmental second-order factors. Model fit statistics for second-order factors and the full model are provided in Table 4.29. CFA model fit statistics such as RMSEA and SRMR were within the traditional cutoff criteria for the Environmental and the Intrapersonal second-order factors (nonsignificant $\chi 2$, CFI $\geq .95$, RMSEA $\leq .06$, SRMR $\leq .08$, and TLI $\geq .95$; Brown, 2015; Browne & Cudeck, 1992; Hu & Bentler, 1999). After combining the Intrapersonal and Environmental second-order factors into one full model, only the RMSEA remained within the rule of thumb cutoff levels. It should be noted, however, that model fit guidelines were developed using only three first-order factors (Hu & Bentler, 1999; Yu, 2002); therefore, it is not surprising that fit statistics for a model with 10 factors and two second-order factors did not fall within these guidelines. Furthermore, as fit statistics vary in relationship to various aspects of the model (e.g., factor loading size, number of factors, degree of misspecification, etc.), some researchers argue that traditional estimates are too conservative for applied research models (Beauducel & Whittman, 2005; Brown, 2015). Methodologists now suggest that CFI and TLI values from .90 to .95 may indicate an acceptable fit (Brown, 2015).

Changes to the model. To assist with model parsimony and ultimately aid with model fit, two other changes were made before SEM could be conducted. Preliminary SEM analysis resulted in an error message indicating that the latent variable covariance matrix was not positive definite because of a problem with the Read at Work factor. Specifically, a negative residual variance indicated that the model was inadmissible and was not suitable for the data (Brown, 2015; Muthén, 2010). According to Brown (2015), some reasons for nonpositive definite covariance matrix include multicollinearity, model misspecification, model complexity, or large amounts of missing data. In a second-order factor analysis, the intercorrelations between factors are the primary interest. Poor fitting models may result when there is not a clear pattern of correlations between the first-order factors that comprise second-order factors. In other words, when an intrapersonal first-order factor such as Learning Motivation has similar-sized correlations with first-order factors comprising Environmental, the second-order factor model is contradicted (Brown, 2015).

In examining the pattern of correlations, two first-order factors, Learning Motivation and Reading at Home, demonstrated the least differences compared to the other first-order factors. Accordingly, the Learning Motivation factor was removed and replaced with a covariate (B_Q12A_T). This option was discussed in Appendix A and was supported by the strong correlation between B_Q12A_T with each of the other Learning Motivation indicators (see Table A.20). Second, the Reading at Home factor was dropped. As expected, these changes resulted in slightly improved CFA model fit statistics: RMSEA = .03, CFI =.90, TLI = .89, SRMR = .08 (see Table 4.29). Furthermore, it was necessary to specify a correlation between the second-order factors given their high degree of interrelatedness (r = .65) to maintain similar fit statistics to results found in each second-order factor CFA. Once these changes were included, the decision was made to proceed with this revised model given that RMSEA, CFI, and SRMR fit statistics were within acceptable levels and that TLI was less than .01 from the more liberal fit statistics referenced by Brown (2015).

Table 4.29

Model Fit Statistics for Second-Order Factors and Full Model

Model	χ2	*df*	RMSEA	CFI	TLI	SRMR
Environmental second-order factor only						
(without covariates)	**3002**	161	.06	.95	.94	.05
(with covariates)	**3471**	313	.04	.93	.92	.06
Intrapersonal second-order factor only						
(without covariates)	**4591**	334	.05	.94	.93	.06
(with covariates)	**5926**	631	.04	.93	.92	.07
Full model with covariates	**14676**	1947	.03	.87	.87	.09
Full model after the following changes						
drop LearnM & ReadH	**9440**	1239	.06	.90	.89	.08
add B_Q12A_T	**9276**	1274	.03	.90	.89	.08

Note. Bold text indicates significance at $p < .05$. See Figure 4.1 and Tables 4.29 and 4.30 for indicator, indicator correlations, and factor correlations.

A graphical representation of the measurement model before and after modification is provided in Figure 4.1. Tables 4.30 and 4.31 display the indicators, factors, and covariates comprising the initial CFA and the revised post hoc model after dropping the Learning Motivation and Reading at Home factors.

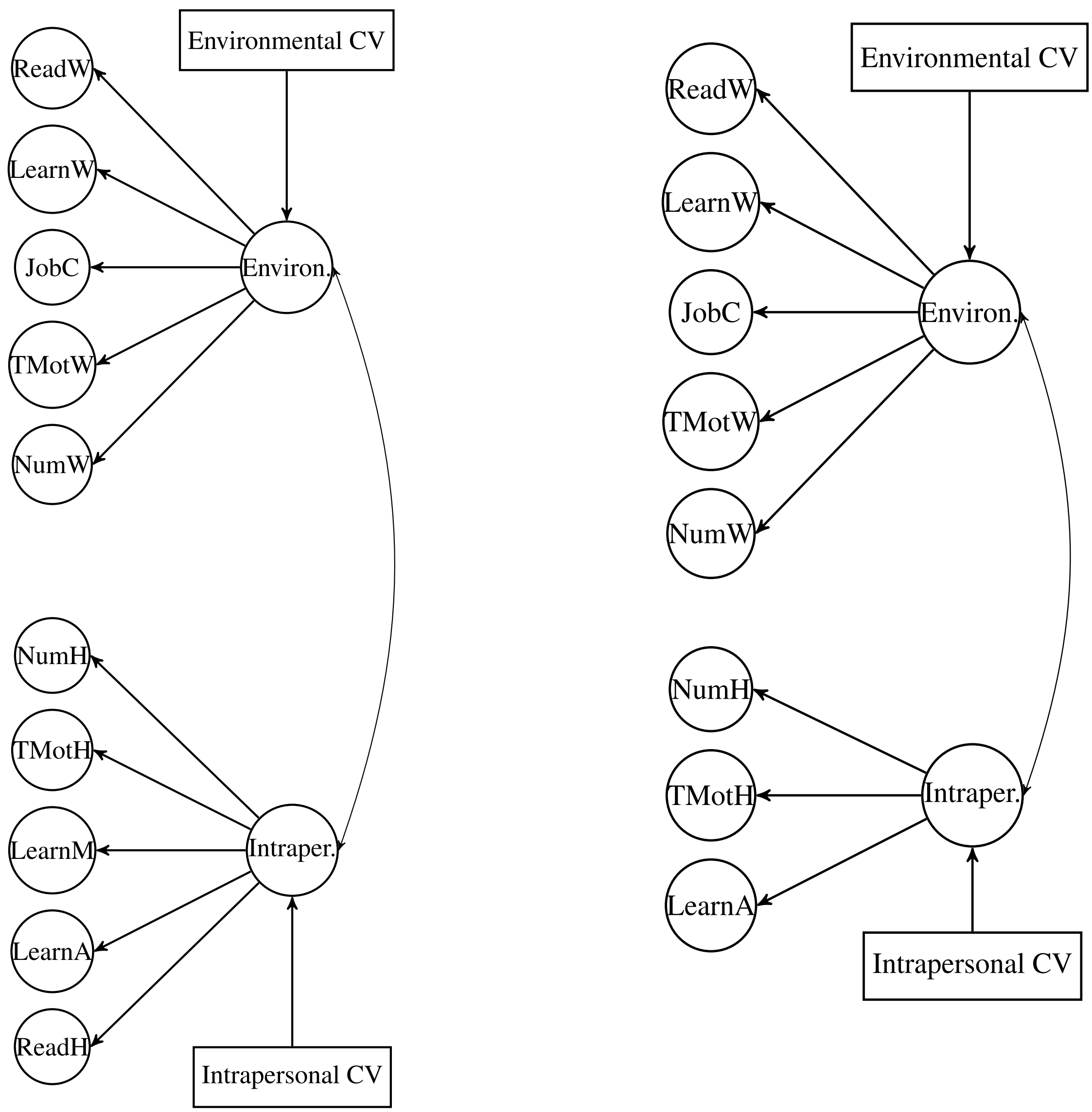

Figure 4.1. Original measurement model (left) and post hoc measurement model after CFA (right). Environmental and intrapersonal covariates (CV) have been drawn as one box to simplify the diagram.

Table 4.30

Environmental Factors, Indicators, and Covariates Used in CFA*

Factor	Item Code and Description
Numeracy at Work (NumW)	G_Q03D use a calculator - either hand-held or computer based
	G_Q03F prepare charts, graphs or tables
	G_Q03G use simple algebra or formulas[1]
	G_Q03H use more advanced math or statistics[1]
	G_Q03B calculate prices, costs or budgets
	G_Q03C use or calculate fractions, decimals or percentages
Reading at Work (ReadW)	G_Q01A read directions or instructions[2]
	G_Q01C read newspapers or magazines[3]
	G_Q01D read articles in professional[3]
	G_Q01E read books
	G_Q01F manuals or reference materials[2]
	G_Q01B read letters, memos, or email
	G_Q01G read financial statements
	G_Q01H read diagrams, maps, or schematics
Technical Motivation at Work (TMotW)	G_Q05C use the internet to collect work-related information
	G_Q05D use the internet to conduct work-related transactions
	G_Q05E use spreadsheets
	G_Q05G use a programming language
Learning at Work (LearnW)	D_Q13A learning new work-related things from co-workers
	D_Q13B learning-by-doing
	D_Q13C keeping up to date
Job Culture (JobC)	F_Q03A planning own activities[4]
	F_Q03B planning others' activities
	F_Q03C organizing own time[4]
	F_Q05B more complex problems

Note. Italicized items were dropped before second-order CFA. [1,2,3,4] Item correlations between specified indicators. *Environmental covariates include education and native birth for mother and father as well as employment status, education, and cultural capital.

Table 4.31

Intrapersonal Factors, Indicators, and Covariates Used in CFA*

Factor	Item Code and Description
Numeracy at Home (NumH)	**H_Q03B calculate prices, costs or budgets[1, 2]** **H_Q03C use or calculate fractions, decimals or percentages[1, 3]** **H_Q03D use a calculator[2, 3]** **H_Q03F prepare charts, graphs or tables** **H_Q03G use simple algebra or formulas[4]** **H_Q03H use more advanced math or statistics[4]**
Technical Motivation at Home (TMotH)	**H_Q05C use the internet to better understand various issues[5]** **H_Q05D use the internet to conduct transactions[5]** **H_Q05E use spreadsheets** **H_Q05G use a programming language write computer code**
Learning Motivation (LearnM)	B_Q12A participated in open or distance education courses B_Q12C attended any organized sessions for on-the-job training B_Q12E participated in seminars or workshops B_Q12G other work- or nonwork-related courses or private lessons ***B_Q12A_T participated in courses outside of program of studies[12]*** *B_Q02A _T1 Education or training in the last 12 months*
Learning Approach (LearnA)	**I_Q04B relate them to real-life situations[6]** **I_Q04D learning new things** **I_Q04H relate to what I already know[6]** **I_Q04J get to the bottom of difficult things[7]** **I_Q04L figure out how different ideas fit together[7]** **I_Q04M look for additional information**
Reading at Home (ReadH)	H_Q01A read directions or instructions[8] H_Q01B read letters, memos, or email H_Q01C read newspapers or magazines H_Q01D read articles in professional journals[9] H_Q01E read books, fiction or non-fiction H_Q01F manuals or reference materials[8, 9. 10] H_Q01G read financial statements[11] H_Q01H read diagrams, maps, or schematics[10,11]

Note. Italicized items were dropped before the second-order CFA. Only bold items are included in the post hoc model. [1-11] Item correlations between specified indicators. *Intrapersonal covariates include age, gender, race, learning disability, vision problems, gender, health, persistence, and native language. [12] B_Q12A_T was added as an intrapersonal covariate in the post hoc model.

CFA interpretation. First-order factors serving as indicators to the second-order Environmental factor will be discussed first, followed by first-order factors serving as indicators to the Intrapersonal second-order factor. The factor loading for each indicator was significant (at *p*s <.001, see Table 4.32). According to Brown (2015), the standardized factor loading can be interpreted as a correlation between the factor and the indicator; therefore, squared factor loadings serve as estimators of the reliability of the indicator and describe the amount of indicator variance explained by the latent construct.

Environmental had five first-order factor indicators. For Numeracy at Work factor, the items with the largest loadings (λs = .76 -.77) indicated that the factor explained 58% to 59% of the variance in the following indicators: use of simple algebra or formulas (G_Q03G); use of more advanced math/statistics (G_Q03H); and preparing charts, tables, or graphs (G_Q03F). The most reliable predictor in the Reading at Work factor was reading articles in professional journals or scholarly publications (G_Q01D; λ^2 = .59 or $.77^2$). Use of the internet at work to collect work-related information (G_Q0C) had the highest correlation (λ = .88) with the Technical Motivation at Work factor. Fifty-nine percent of the variance in indicator D_Q13C, keeping up to date with new products or services, was explained by the Learning at Work factor. The Job Culture/Problem Solving at Work factor demonstrated a strong correlation with all factors (λs = .60 to .67); solving complex problems (F_Q05B) showed the highest reliability (λ^2 = .45 or $.67^2$) of the Job Culture factor.

Although there were originally five factors comprising Intrapersonal, two were dropped for reasons previously explained (see *Changes to the Model* section). For the

Table 4.32

Standardized First-Order Factors

Factor and Indicator	λ	*SE*	*p*	95% CI
Intrapersonal				
NUMH_BY				
H_Q03F	0.73	0.02	0.00	0.70 - 0.77
H_Q03B	0.47	0.02	0.00	0.43 - 0.51
H_Q03C	0.68	0.02	0.00	0.65 - 0.71
H_Q03D	0.64	0.02	0.00	0.61 - 0.67
H_Q03G	0.75	0.02	0.00	0.72 - 0.78
H_Q03H	0.75	0.02	0.00	0.71 - 0.79
TMOTH BY				
H_Q05E	0.77	0.02	0.00	0.74 - 0.80
H_Q05C	0.62	0.02	0.00	0.58 - 0.65
H_Q05D	0.57	0.02	0.00	0.53 - 0.60
H_Q05G	0.74	0.03	0.00	0.69 - 0.80
LEARNAP BY				
I_Q04D	0.79	0.01	0.00	0.77 - 0.81
I_Q04B	0.68	0.01	0.00	0.65 - 0.71
I_Q04H	0.74	0.01	0.00	0.72 - 0.76
I_Q04J	0.72	0.01	0.00	0.69 - 0.74
I_Q04L	0.79	0.01	0.00	0.77 - 0.81
I_Q04M	0.73	0.01	0.00	0.71 - 0.75
Environmental				
NUMW_BY				
G_Q03F	0.77	0.01	0.00	0.75 - 0.80
G_Q03D	0.71	0.01	0.00	0.69 - 0.74
G_Q03G	0.76	0.01	0.00	0.73 - 0.78
G_Q03H	0.76	0.02	0.00	0.73 - 0.79
READW_BY				
G_Q01D	0.77	0.01	0.00	0.75 - 0.80
G_Q01A	0.58	0.02	0.00	0.54 - 0.61
G_Q01C	0.69	0.02	0.00	0.66 - 0.72
G_Q01E	0.57	0.02	0.00	0.54 - 0.60
G_Q01F	0.66	0.01	0.00	0.64 - 0.69
TMOTW_BY				
G_Q05C	0.88	0.01	0.00	0.86 - 0.90
G_Q05D	0.67	0.02	0.00	0.64 - 0.70
G_Q05E	0.79	0.01	0.00	0.77 - 0.81
G_Q05G	0.68	0.02	0.00	0.63 - 0.72
LEARNW BY				
D_Q13C	0.77	0.02	0.00	0.72 - 0.81
D_Q13A	0.54	0.02	0.00	0.49 - 0.58
D_Q13B	0.65	0.02	0.00	0.61 - 0.69
JOBC_BY				
F_Q05B	0.67	0.02	0.00	0.64 - 0.70
F_Q03A	0.64	0.02	0.00	0.61 - 0.68
F_Q03B	0.64	0.02	0.00	0.61 - 0.67
F_Q03C	0.60	0.02	0.00	0.56 - 0.64

Numeracy at Home factor, the two items with the largest loading (λs = .75) indicated that 56% of the variance in the use of simple algebra or formulas (H_Q03G) or in use of more advanced math/statistics (G_Q03H) was explained by the factor Numeracy at Home. Use of spreadsheets (H_Q05E) was the indicator that had the highest correlation (λ = .77) with Technical Motivation at Home. Finally, the Learning Approach factor explained 62% of the variance for two indicators (λs = .79): enjoying learning new things (I_Q04D) and figuring out how different ideas fit together (I_Q04L).

Item-level and factor-level correlations were also examined. Correlations between first-order factor indicators were specified in accordance with theory as described in Appendix A. Table 4.33 presents the results from the specified correlations. The specified correlation between the second-order factors, Intrapersonal with Environmental, demonstrated a strong relationship ($r_{\text{env, intra}}$ = .65). Correlations between first-order factors and second-order factors are reported in Table 4.34.

In a second-order CFA, first-order factors are assumed to be intercorrelated. In fact, there would not be a reason to use higher-order factor analysis if no relationships were observed among the first-order factors (Brown, 2015). Table 4.34 shows the pattern of correlations between intrapersonal factors in which Numeracy at Home, Learning Approach, and Technical Motivation at Home are more strongly related to each other (Φs = .42 - .71) and to Intrapersonal (Φs = .53 - .89.). Similarly, Numeracy at Work, Reading at Work, Technical Motivation at Work, Learning at Work, and Job Culture have stronger correlations with one another (Φs = .46 - .75) and to Environmental (Φs = .59 - .88).

Table 4.33

Correlations Specified in the Model

Indicator	ϕ	*SE*	*p*	95% CI
ENV WITH INTRA	0.65	0.02	0.00	0.61 - 0.68
Numeracy at Home				
H_Q03B WITH H_Q03C	0.48	0.02	0.00	0.45 - 0.51
H_Q03B WITH H_Q03D	0.26	0.02	0.00	0.22 - 0.30
H_Q03G WITH H_Q03H	0.36	0.03	0.00	0.30 - 0.43
H_Q03D WITH H_Q03C	0.24	0.02	0.00	0.20 - 0.28
Technical Motivation at Home				
H_Q05C WITH H_Q05D	0.50	0.02	0.00	0.47 - 0.54
Learning Approach				
I_Q04J WITH I_Q04L	0.35	0.02	0.00	0.31 - 0.39
I_Q04B WITH I_Q04H	0.32	0.02	0.00	0.28 - 0.36
Numeracy at Work				
G_Q03G WITH G_Q03H	0.37	0.03	0.00	0.30 - 0.43
Reading at Work				
G_Q01A WITH G_Q01F	0.34	0.02	0.00	0.30 - 0.37
G_Q01C WITH G_Q01D	0.45	0.02	0.00	0.41 - 0.49
Job Culture				
F_Q03A WITH F_Q03C	0.64	0.02	0.00	0.61 - 0.68

Table 4.34

Correlations Between Factors (Phi Matrix)

Factors	NUM H	TMOT H	LEARN AP	INTR A	NUM W	READ W	TMOT W	LEARN W	JOB C
NUMH	1.00								
TMOTH	.71	1.00							
LEARN AP	.42	.47	1.00						
INTRA	.80	.89	.53	1.00					
NUMW	.36	.40	.24	.45	1.00				
READW	.35	.39	.23	.44	.75	1.00			
TMOTW	.35	.39	.23	.44	.75	.73	1.00		
LEARN W	.24	.27	.16	.31	.52	.51	.51	1.00	
JOBC	.32	.35	.21	.40	.67	.66	.66	.46	1.00
ENV	.41	.46	.27	.51	.88	.85	.86	.59	.77

Residual variances, or the estimated error variance for the first-order factors, were also examined. Given larger squared loading values for the first-order factors compared to the second-order factors, it is clear the first-order factors did a better job explaining the shared variance among their indicator items compared to the second-order factors (see Table 4.35). Larger residual variances for Intrapersonal and Environmental indicated that much of the outcome, Numeracy Achievement, is unexplained. The overall model pseudo-R^2 value of .09 (SE = .03; p < .001) may also support this assumption. The factors that appeared to explain the shared variance the best were Technical Motivation at Home, Numeracy at Work, Technical Motivation at Work, and Reading at Work.

Table 4.35

Factor Squared Loadings and Residual Variances

Indicator	λ^2	*SE*	*p*		ε	*SE*	*p*
Squared Loadings				Residual Variance			
Intrapersonal				*Intrapersonal*			
INTRA	0.23	0.02	0.00	INTRA	0.77	0.02	0.00
NUMH	0.64	0.03	0.00	NUMH	0.36	0.03	0.00
TMOTH	0.79	0.03	0.00	TMOTH	0.21	0.03	0.00
LEARNAP	0.28	0.02	0.00	LEARNAP	0.72	0.02	0.00
Environmental				*Environmental*			
ENV	0.21	0.01	0.00	ENV	0.79	0.01	0.00
NUMW	0.77	0.02	0.00	NUMW	0.23	0.02	0.00
READW	0.73	0.02	0.00	READW	0.27	0.02	0.00
TMOTW	0.74	0.02	0.00	TMOTW	0.26	0.02	0.00
LEARNW	0.35	0.02	0.00	LEARNW	0.65	0.02	0.00
JOBC	0.59	0.02	0.00	JOBC	0.41	0.02	0.00

Standard errors were also examined. All standard errors were very small, ranging from .01 to .03 (see Tables 4.32, 4.33, 4.35 and 4.36). Given very little variability, we can be confident that the data reflects the population.

Lower-order factors act upon higher-order factors similar to indicators in a single-factor model (Brown, 2015). Each of the first-order factors loaded moderately to strongly on the second-order factors (see Table 4.36). The range of loadings for factors serving as indicators for the Intrapersonal factor was .53 to .89, and the range of loadings for factors serving as indicators for the Environmental factor was .59 to .88. Covariate effects are discussed in the SEM section.

Structural Equation Modeling

Following CFA, SEM was conducted to predict the categorical outcome of scoring at the highest numeracy group level (i.e., being in the top 10% of numeracy proficiency) or not. As described in the data analysis section of Chapter Three, the initial SEM used only the first set of plausible values. Next, SEM was conducted for the full model using all 10 sets of plausible values and sample weights.

SEM Using One Set of Plausible Values

The first SEM was weighted with sample weights (SPFWT0) but was conducted using only one set of plausible values. This SEM analysis terminated normally. Model fit statistics are reported: $\chi 2$ (1328) = 9,654, $p < .05$; RMSEA = .03; CFI = .89; TLI = .89; SRMR = .09.

Table 4.36

Standardized Second-Order Factor CFA Results

FACTOR Indicator	λ	*SE*	*p*	95% CI
INTRA BY				
NUMH	0.80	0.02	0.00	0.77 - 0.83
TMOTH	0.89	0.02	0.00	0.86 - 0.92
LEARNAP	0.53	0.02	0.00	0.49 - 0.57
ENV BY				
NUMW	0.88	0.01	0.00	0.86 - 0.90
TMOTW	0.86	0.01	0.00	0.84 - 0.88
READW	0.85	0.01	0.00	0.83 - 0.88
JOBC	0.77	0.02	0.00	0.74 - 0.80
LEARNW	0.59	0.02	0.00	0.55 - 0.63
INTRA ON				
GENDER_R	-0.11	0.02	0.00	-0.14 - -0.07
I_Q08USX3	-0.05	0.02	0.01	-0.08 - -0.01
I_Q08USX1	-0.03	0.02	0.17	-0.07 - 0.01
AGEG10LFS_	-0.18	0.02	0.00	-0.22 - -0.14
NATIVELANG	-0.09	0.03	0.00	-0.15 - -0.03
BLACK	0.07	0.02	0.00	0.03 - 0.11
HISPANIC	0.03	0.03	0.34	-0.03 - 0.07
OTHERRACE	0.04	0.02	0.04	0.00 - 0.08
UNCOMPLETE	0.17	0.02	0.00	0.13 - 0.21
PRESSTUDY	0.27	0.02	0.00	0.24 - 0.31
I_Q08	-0.11	0.02	0.00	-0.15 - -0.08
B_Q12A_T	0.17	0.02	0.00	0.13 - 0.21
ENV ON				
J_Q06BUS	-0.03	0.02	0.13	-0.08 - 0.01
J_Q06A	-0.01	0.03	0.70	-0.08 - 0.05
J_Q07BUS	0.03	0.02	0.10	-0.01 - 0.08
J_Q07A	-0.01	0.03	0.78	-0.08 - 0.06
J_Q08	0.10	0.02	0.00	0.06 - 0.14
EDCAT6	0.40	0.02	0.00	0.36 - 0.44
UNEMPLOYED	-0.06	0.01	0.00	-0.07 - -0.04
OUTOFWORKF	-0.06	0.01	0.00	-0.08 - -0.04

SEM Using All Sets of Plausible Values

Subsequently, another SEM analysis was conducted using all 10 sets of plausible values and applying sample weights. The resulting model fit statistics were essentially the same [$\chi 2$ (1328) = 9,636, $p < .05$; RMSEA = .03; CFI = .89; TLI = .89; SRMR = .09]. Standardized solutions are presented in the following tables in accordance with Brown's (2015) recommendation on reporting second-order factors.

The standardized effect of the second-order factors is reported first. The effect of Environmental on Numeracy was equivocal given a nonsignificant p-value (γ = -0.08, p = .26) (see Table 4.37 and Figure 4.2). Furthermore, the 95% confidence interval [-.21, .06] indicated potential positive or negative effects on numeracy achievement. A small to moderate positive effect of Intrapersonal (γ = .33, 95% CI [.19, .47]) indicated that when Intrapersonal increases, the likelihood of being in the top 10% increases.

Table 4.37

Standardized Structural Model SEM Results

Factor	γ	*SE*	*p*	95% CI
NUMERACY PROFICIENCY ON				
ENV	-0.08	0.07	0.26	-0.21 - 0.06
INTRA	0.33	0.07	0	0.19 - 0.47

Most relationships are unchanged from the CFA. The item loadings to first-order factors are the same as previously described in the CFA interpretation section (see Table 4.32). Residual variances and correlations remained the same (see Tables 4.33 to 4.35). First-order factor loadings onto the second-order factors were unchanged as well (see Table 4.36). Besides the addition of the outcome variable, the only results that changed were the covariates because of indirect relationships to Numeracy.

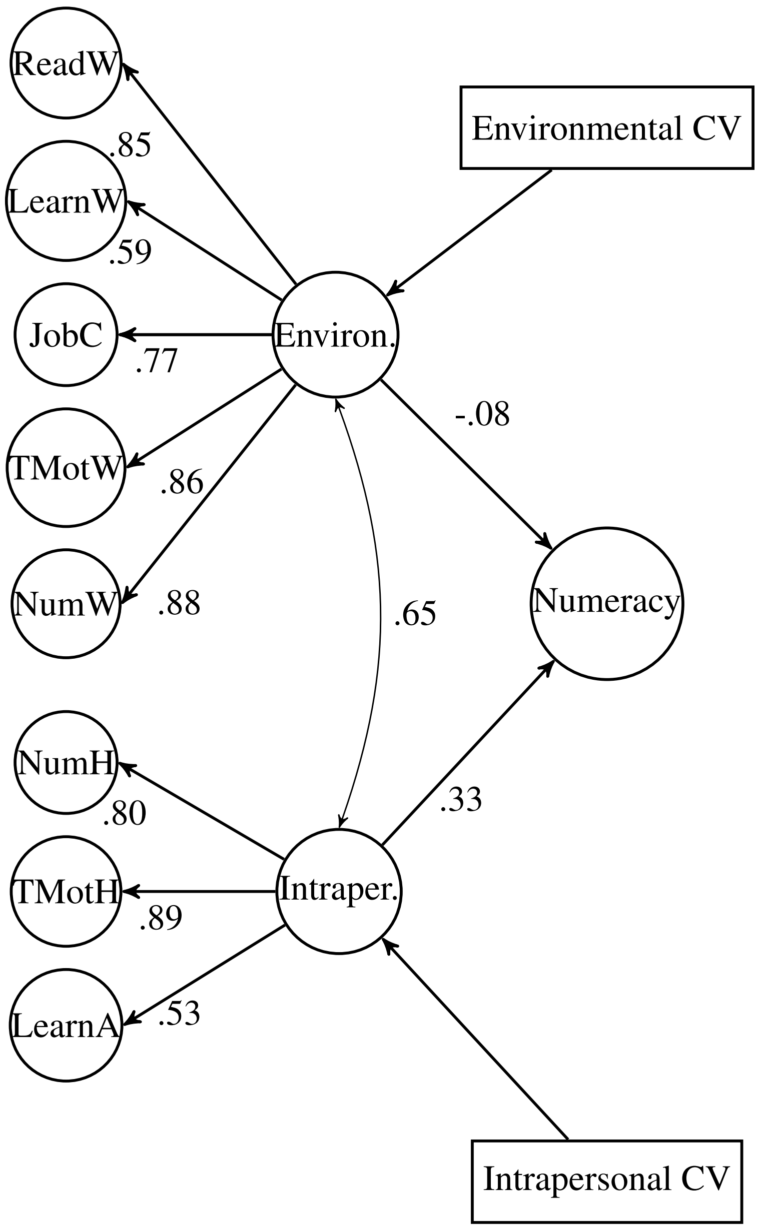

Figure 4.2. Adult Numeracy Achievement Model with standardized SEM results for first-order and second-order factors. Environmental and intrapersonal covariates were each drawn as one box to simplify the model. Environmental covariates include education and native birth for mother and father as well as employment status, education, and cultural capital. Intrapersonal covariates include age, gender, race, learning disability, vision problems, gender, health, persistence, native language, and learning motivation.

Covariates to Environmental. The environmental covariates, except for two items, had little if any positive effect on the second-order Environmental factor (see Table 4.37). Holding everything else constant, there was a moderate effect of terminal education (EDCAT6) on Environmental and a small effect of the number of books in the home at age 16 (J_Q08). Given nonsignificant *p*-values and 95% confidence intervals that encompass both negative and positive values, no effect on Environmental is found for mother's education (J_Q06BUS), father's education (J_Q07BUS), or if one's mother or father was born in the United States (J_Q06A, J_Q06B). Being unemployed or being out of the workforce had a very small negative effect on Environmental. However, given a nonsignificant effect of Environmental to Numeracy, it is difficult to substantiate conclusions regarding the indirect effect of environmental covariates on numeracy achievement.

Covariates to Intrapersonal. Covariate effects to the second-order Intrapersonal factor were also mixed. The largest positive effect on Intrapersonal was if the individual was enrolled in a degree-seeking program as compared to being employed (see Table 4.37), holding all other items constant. Surprisingly, there was also a small positive effect of discontinuing a degree (UNCOMPLETE) as compared to being employed. Another small positive effect was the participation of courses outside the participant's program of studies (B_Q12A_T). Age had a negative effect on Intrapersonal, meaning that as individuals aged into the next 10-year age bracket their Intrapersonal value would decrease when all other variables were held constant. Females, compared to males, had a small negative effect on Intrapersonal. A small negative effect was also found for taking the competency assessment in a non-native language. With respect to race, a very small positive effect was found for Black (as compared to White) but no effect for any other race. As health (I_Q08) was coded from excellent to poor, the negative effect of health, in reality, means that better health is associated with increased Intrapersonal. The presence of a learning disability (I_Q08USX3) had a very small negative effect on Intrapersonal. There were no effects of vision problems (I_Q08USX1). It must be remembered that these are not direct effects on Numeracy achievement but are indirect effects on Intrapersonal.

Indirect effects of the covariates on Numeracy are more difficult to assess. Although indirect effects of a covariate to Numeracy via Intrapersonal are straightforward, indirect effects of a covariate on Numeracy via Environmental are not as clear for reasons already specified. For intrapersonal covariates with an interval scale, the indirect effect of the covariate on Numeracy through Intrapersonal can be determined by multiplying the covariate path value by the Intrapersonal path value ($\gamma = .33$). For example, the indirect effect of age on Numeracy is -.06 (-.18 x .33), meaning that for each age band increase there is a decreased likelihood of being in the top 10% numeracy group. The indirect effect of health on Numeracy is -.04 (-.11 x .33), meaning when all other items are held constant, those who reported poorer health have a decreased likelihood of being in the top 10% numeracy group. When interpreting dummy coded variables, all reference categories (i.e., code = 0; male, no learning disability, native speaker, White, completed degree program) had no value for indirect effects of the covariate to Intrapersonal. For dummy-coded covariate categories equal to 1 with negative path values (e.g., with learning disability, non-native speaker, female) there was a net effect of a decreased likelihood of scoring in the top 10% in numeracy as compared to those who did not have a learning disability, were native speakers, or who were male.

The indirect effects of first-order factors or their predictors on Numeracy were also difficult to interpret in a meaningful way given the model structure. For example, the direction of the arrows in Figure 4.2 demonstrates that a path cannot be drawn to determine the indirect effects of the first order factors on numeracy achievement.

Conclusion

This chapter reported the descriptive statistics and the results of confirmatory factor analysis, and structural equation modeling. As a result of CFA, changes were made to individual first-order factors. Reasons for these modifications to the original model were explained. As a result, a post hoc Adult Numeracy Achievement Model was presented. Chapter Five will summarize and situate findings within the context of relevant literature.

CHAPTER FIVE

Discussion

This study sought to discern the effects of environmental and intrapersonal characteristics on the numeracy skills of the highest performing U.S. adults compared to lower-performing adults. Numeracy is the ability to interpret and communicate mathematical ideas, apply math skills, and solve problems with numbers in a real-world context (OECD, 2012). American adults have lower numeracy skills compared to other nations, ranking 18 of 22 participating countries (Rampey et al., 2016).

Numeracy skills are essential at the individual, community, and national level. Past research suggests a positive relationship between numeracy skills and other items at the individual level such as employment, earnings, health, computer skills, and computer use (Bynner & Parsons, 1997; Carpentieri et al., 2010; National Numeracy, 2018; Parsons & Bynner, 2005). At the community level, individuals who lack basic numeracy skills are more likely to have children who lack basic numeracy skills, more likely to be homeless, less likely to vote or participate in community organizations, and up to 5 times more likely to be unemployed or opt out of the labor market (Bynner & Parsons, 1997; DfEE, 1999). At the national level, increasing numeracy is linked to greater participation in adult education, increased average worker productivity, and a higher GDP (Coulombe et al., 2004; DfEE, 1999; OECD, 2013a). Researchers estimate that enhancing the math proficiency of American students could equate to a $75 trillion increase in national income over the next 80 years (Peterson, Woessmann, Hanushek, & Lastra-Anadón, 2011).

Carpentieri et al. (2010) reiterated Coben's (2003) earlier conclusion that "adult numeracy is under-researched and under-theorised" (p. 7). Furthermore, the limited research that has been done focused on individuals with numeracy deficits rather than examining the highest performers. The purpose of this study was to investigate the relationships between numeracy proficiency, environmental and intrapersonal characteristics of the highest performing adults on numeracy achievement. In accordance with Gagné's (1985, 2000, 2012) Differentiated Model of Giftedness and Talent, individuals scoring in the top 10% of numeracy from the U.S. sample of the Program for the International Assessment of Adult Competencies (PIAAC) survey were compared with the remaining population of adults to examine aspects related to developing talent. The goal of this study was to empirically test the predictive potential of two overarching factors of talent development: Environmental (e.g., family, SES, etc.) and Intrapersonal (e.g., interests, learning approach, motivation, etc.). This study sought to answer three primary questions:

1.0 What are the characteristics of U.S. adults who perform in the top 10% in numeracy proficiency?

2.0 What are the characteristics of U.S. adults who perform below the 90th percentile in numeracy proficiency?

3.0 To what extent do environmental characteristics and intrapersonal characteristics predict differences in numeracy proficiency for U. S. adults?

Through the use of descriptive statistics, the first two research questions addressed environmental and intrapersonal characteristics associated with individuals performing at the top 10% in numeracy compared to individuals performing below the 90th percentile. The third question used Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to examine the effects of environmental and intrapersonal characteristics using the post hoc conceptual model shown in Figure 5.1.

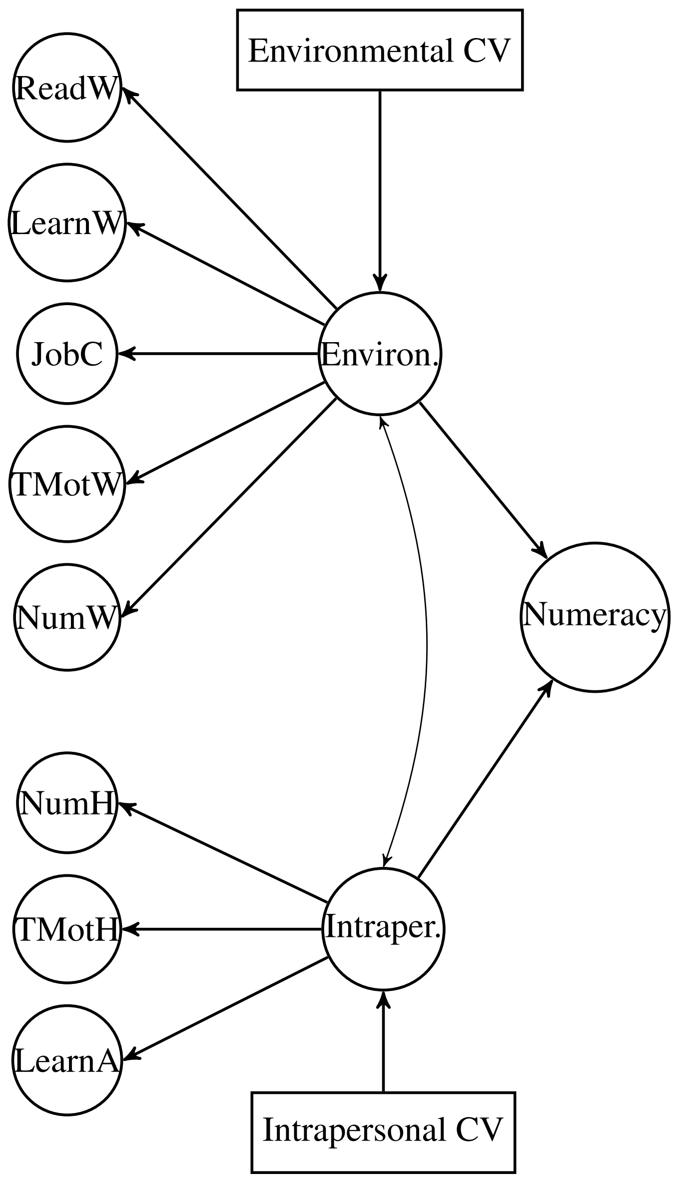

Figure 5.1. Post hoc Adult Numeracy Achievement Model. Environmental covariates include education and native birth for mother and father as well as employment status, education, and cultural capital. Intrapersonal covariates include age, gender, race, learning disability, vision problems, health, persistence, native language and learning motivation.

This chapter gives an overview of the results of the study situated within the context of the literature that guided this study. Other pertinent literature is also added. Methodological implications are discussed in order to improve future studies using PIAAC data or studies addressing adult numeracy achievement. The chapter concludes with sections that describe the research limitations, practical implications, and areas for future study.

Environmental Findings

Environmental Background

An individual's background is theorized to influence long-term performance (Gagné, 1985; Tannenbaum, 1983). Much research has examined the relationship between outcomes and family background variables. The most often studied characteristics typically relate to parent education levels and socioeconomic status. This study examined childhood characteristics related to immigrant parents, parent education, and the number of books in participants' childhood homes. Participants' adult background included their terminal education and employment status.

Foreign-born parents. The results from the descriptive statistics show differences in numeracy performance related to whether or not participants had a foreign-born father. The top 10% group was significantly more likely to have a father who had been born in the United States, whereas no difference was detected for mother's birthplace. Similarly, Rothman and McMillan (2003) found no effect for mother's birthplace on numeracy achievement in high school. On the other hand, researchers in gifted education report that it is not uncommon for adults who are highly gifted in STEM fields to have a foreign-born parent (28%-41%, Feist, 2006; Lubinski et al., 2006). Yet, Campbell and Feng (2010) found no difference in Olympiad performance between children of immigrants, noting that most participants were third-generation Americans. Although prior descriptive research and descriptive statistics from this study suggest that a non-native father may be a predictor of gifted-level numeracy skills, the results of the SEM indicate that neither a foreign-born mother nor a foreign-born father is significant.

Parent education. In this study, descriptive statistics show that the top 10% group are significantly more likely to have a mother or father who earned a college degree and less likely to have a mother or father who did not complete high school compared to the less numerate group. The United States, compared to all other PIAAC participating countries, has the largest numeracy skills gap between parents with high education levels compared to parents with less than a high school degree (OECD, 2013a). These descriptive findings on parental education are consistent with results from previous international survey research with youth (e.g., PISA performance) and adults (e.g., ALL and IALS performance) (OECD, 2013a).

The majority of prior research indicates that an individual's terminal education is highly related to parental education attainment (Davis-Kean, 2005; Dubow, Boxer & Huesmann, 2009; Haveman & Wolfe, 1995). Compared to individuals with good numeracy skills, the likelihood of scoring at the very lowest levels of numeracy was 1.5 greater for individuals whose mothers did not attend postsecondary education (Carpentieri et al., 2010; Parsons & Bynner, 2007). Even among the most gifted in math and sciences, the more successful adults were more likely to have parents who earned a college degree (Benbow & Arjmand, 1990; Kaufmann, 1981; Terman, 1954).

Despite the descriptive statistics and prior research indicating a potential difference between groups, according to this study's numeracy achievement model, parent education level was nonsignificant for predicting numeracy achievement. Similarly, Rothman and McMillan's (2003) model also showed no effect of parent education on youth numeracy skills, but the researchers suggested the effect was diminished because of correlation with other variables including a SES item. Using similar logic, it may be that one or more other covariates are sharing large amounts of variance with parent education, and therefore, parent education is redundant. Although OECD (2013a) indicates the PIAAC uses mother and father educational attainment as a proxy for SES, Carnoy and Rothstein (2013) argue that the books in the home item is a better proxy for social class than parent education based on their examination of PISA mathematics performance.

Number of books in childhood home. This results of this study suggest that the number of books in participants' homes at age 16 may be associated with adult numeracy performance. For example, the greatest differences between the top 10% group and the below 90th percentile group were the percentage who reported the fewest books and the percentage who reported the most books in their childhood homes. Highly numerate individuals were less likely to report having fewer than 25 books in their home at age 16 and were more likely to report having 100 or more books as compared to the lower numeracy group.

The number of books in a childhood home is an indicator of cultural capital used in other international surveys (e.g., PISA and TIMSS) and is consistent with Bourdieu's (1984) conception of cultural capital which often serves as a predictor of academic performance (OECD, 2011). Cultural capital is typically acquired through interacting with other members of one's social class and, therefore, hinders social mobility and perpetuates inequality. Middle-class and upper-class parents usually provide books which help to and develop cultural and language competence (OECD, 2011). Even among the most highly able, Terman (1954) found the more successful had 50% more books in their homes than the less successful group. Campbell and Feng (2010) also found that more successful former-Olympiads had an abundance of books in their childhood homes and were from higher SES homes compared to the less successful former Olympiads.

Socioeconomic diversity in childhood homes is rare in the gifted adult research but much more common in the numeracy field. Terman's (1926) high IQ children were from middle to upper-class households. The SMPY parents "were typically highly educated [and] fathers held high paying jobs" (Benbow & Arjmand, 1990, p. 432). At the lowest end of performance, Parsons and Bynner (2007) used the longitudinal 1970 British Cohort study to determine the characteristics of youth who had poor numeracy skills at age 34 and found that individuals with the lowest numeracy skills were twice as likely to have received free school meals at age 10 and have parents who received unemployment benefits. Those with the weakest skills at age 34 were less likely to have been raised in a parent employed in a professional job and more likely to have a parent employed in an unskilled profession compared to those with good skills.

The descriptive results and prior research appear to indicate differences in numeracy performance. The more successful of the highly gifted also had more books in their childhood homes. Indeed, if this variable were a proxy for SES, then it would likely be expected to be a predictor of numeracy performance. In fact, the number of books had the second largest effect of the environmental covariates. Despite an effect of books in the childhood home on the second-order Environmental factor, the indirect effect on numeracy achievement is undetermined because of the nonsignificant path value from Environmental to Numeracy.

Terminal education. Not surprisingly, this study's descriptive statistics show differences between education attainment in the higher and lower numeracy ability groups. Prior research has already suggested that individuals with higher numeracy levels are more likely to have earned a postsecondary degree (Bynner & Parsons, 2006; Carpentieri et al., 2010). Most (73%) of the highly numerate group in this study had earned a terminal professional, bachelor, or master's degree compared to 32% of the lower numeracy group. These percentages include approximately 30% of the high numerate group and 8% of the lower numerate group who earned a graduate degree. Surprisingly, 20% of the most proficient in numeracy had only earned a terminal high school diploma. These findings highlight that numeracy proficiency is positively related to educational attainment, but high overall educational attainment is not always necessary to score at the highest levels in numeracy. Those in the lower group, however, were 2 times more likely to have discontinued education after a high school diploma and 15 times more likely to have less than high school education.

These findings are not entirely consistent with the educational degree attainment of the highest performers in the gifted literature (Lubinski & Benbow, 2006). Most of the top 1% prior-SMPY participants earned their bachelor's degree (85%-95%, depending on the cohort) and 37% to 60% earned a master's or doctoral degree. Several reasons are suggested for these discrepancies: (a) the SMPY sample followed a more selectively identified group (top 1% ability-level or those in elite graduate programs) and Wai et al., (2005) reported that the percentage of postsecondary degrees grows with increasing ability levels; (b) SMPY results are based on participant responses to a questionnaire at age 33 and do not reflect all of the original participants (18-22% attrition); (c) PIAAC participants range from 16-65 and include many who are too young to have completed postsecondary or graduate education; and (d) PIAAC percentages are weighted to reflect the entire U.S. population. One possible explanation for the surprising percentage of individuals who only had a high school diploma yet still scored at the highest numeracy level is that many of those individuals were pursuing a college degree but had not yet completed it, or perhaps on-the-job training enabled these individuals to continue to develop numeracy. If most of the 20% who only have a high school diploma eventually complete a bachelor's degree, then the percentages might be more consistent with the previous literature.

Although gifted literature descriptive research show higher levels of educational attainment, participants are from more selective samples and responded in midlife (vs. PIAAC's cross-sectional study). Nevertheless, educational attainment is the strongest environmental covariate. Given a nonsignificant path to Environmental, the model does not conclusively support an effect of education on numeracy achievement.

Employment. According to the IDE descriptive analysis representing all U.S. respondents, the top 10% are more likely to be employed, which is consistent with other research related to numeracy abilities and employment (Bynner & Parsons, 2006; Carpentieri et al., 2010). Similarly, those with lower numeracy abilities are more likely to be unemployed or out of the labor market. According to descriptive statistics for this study's employed sample, there were no differences between the higher and lower numeracy groups, which is not surprising because the sample for this study is limited to those who were employed in the prior 12 months. The highly numerate group was more likely to be employed in skilled jobs and less likely to be in semi-skilled or elementary occupations. Numeracy skills, however, can develop after completion of terminal education, especially if one's occupation requires it (Carpentieri et al., 2010). Conversely, numeracy skills decline if they are not used in employment (Bynner & Parsons, 1998; DfES, 2004).

Previous research has found that numeracy and employment are positively related. For example, individuals in the United Kingdom with the lowest numeracy skills were 2 times more likely to be unemployed compared to those with good literacy skills (Carpentieri, 2010). In fact, numeracy skills were be more important in predicting employment in the United States compared to soft skills such as communication, collaboration, creativity, innovation, and critical thinking (Sulak, Wilson, Renbarger, Kaul, & O'Guinn, in press).

It is unclear how our findings compare with those reported in the gifted literature. It is curious that Benbow et al. (2000) offered no explanation for the difference between the respondents (*n* = 1593 in Cohort 1 and *n* = 592 in Cohort 2) and those the number who were employed or working as a homemaker (*n* = 1284 in Cohort 1 and *n* = 532 in Cohort 2); perhaps these results were an error or perhaps 18% of Cohort 1 and 10% of Cohort 2 were unaccounted for or unemployed. Homemakers, who opted out of the workforce accounted for 13%-15% of SMPY respondents at age 33. By age 48-53, approximately 3%-5% of responding former SMPY participants were unemployed, and 2%-10% were retired or a full-time homemaker (Lubinski et al., 2014).

The results of this study may support a small employment effect on Environmental. This is suggested because a negative effect on the second-order Environmental factor was observed for individuals who were unemployed or out of the workforce. However, the nonsignificant path from Environmental to Numeracy prevent conclusive statements.

Environmental Demographics Not Included in the Model

Multiple variables are reported for descriptive purposes only and were not included in the model for various reasons. Although income is theorized to impact one's talent development, because of the high percentage of missing data, it was not included in the SEM because it would significantly reduce sample size. Information on participants' marriage/partner status and children was reported as a point of comparison only as these items are not theorized to impact talent development directly.

Income. Prior research has demonstrated that individuals who lack basic skills such as numeracy or literacy earn less, but poor numeracy skills have a greater impact on earnings or lack of earnings compared to poor literacy (OECD, 1997). In fact, OECD (2013) reported a 12% increase in income for every standard deviation increase in numeracy ability (52.6 points), even after controlling for other factors including gender, education level, and non-native birth. It was not surprising, therefore, that almost half of the highly numerate participants' annual household income was in the highest quintile compared to only 16% in the lower numeracy group. One caveat is that that data for this item may not be reliable given the higher percentage of missing responses. According to the U.S. Census Bureau (2018), the approximate upper limit for each of the annual household income quintiles in 2014 was (a) $21,000, (b) $41,000, (c) $68,000, and (d) $112,000. Household incomes greater than $206,000 were in the top 5%.

For comparison sake, former SMPY participants reported their income in 2012-2013 (Lubinski et al., 2014). Although the range of income was not reported in the article, the median household income was above $190,000 for male and $184,000 for female participants. Interpreting these values in light of the U.S. Census cutoffs, it is apparent that over 50% of respondents reported a household income in the top quartile in midlife. Again, one must remember differences when attempting to make direct comparisons: (a) the SMPY sample is more selective (i.e., top 1%) compared to this study's top 10%, (b) income typically increases over adulthood and the SMPY sample was 48-53 years old whereas the PIAAC sample included participants ages 16 to 65, and (c) PIAAC data have been calibrated to reflect the U.S. population.

Marriage/living with partner. Participant family status is not theorized to contribute to their numeracy abilities but was reported as a point of reference. Approximately 7% to 13% fewer of the high numeracy group reported living with a spouse/partner compared to the lower numeracy group. Although descriptive research from the gifted adult literature is scant, results are difficult to compare directly because of the wording of questions on different surveys. PIAAC asked if the participant was living with their spouse or partner, but other studies ask if the participant is married or the study includes multiple categories such as divorce, civil union, or domestic partnership. Most former SMPY participants (72%-81%) were married or in long-term relationships in their mid-30s (Benbow et al., 2000). Over 90% of former Presidential Scholars were married/in marriage-like relationships compared to 71% of same-age/same-educational attainment peers in their 50s and 60s (Kaufmann & Matthews, 2012, p. 87).

Children. Significantly fewer highly numerate individuals (55%) had children or stepchildren compared to 66% of the less skilled. In the below 90th percentile group, individuals who were not living with a spouse/partner or did not have children scored significantly higher in average numeracy compared to those who were living with a spouse/partner or who did have children. Overall the high numeracy group also had fewer children, on average, than the lower group.

This finding may be related to socioeconomic status or a delay due to prolonged education. Parents who are employed in semi-skilled or skilled jobs are more likely to have more children than those in professional occupations (Berk & Meyers, 2016). Carpentieri et al. (2010) reported that women in the lowest numeracy group were 2 times more likely to have a child as a teen and 3 times more likely compared to women with good numeracy to have four or more children by age 34. Gifted adults reported fewer children compared to their average-ability peers. While over 60% had no children by their early 30s (Lubinski et al., 2006), this percentage decreased to about 25% by midlife (Lubinski et al., 2014). Over 77% of former Presidential Scholars had children by their mid-40s, but only 25% of the original cohort responded (Kaufmann & Matthews, 2012).

Environmental Factors - Skill Use at Work

Interestingly, Goodman et al. (2013) asserted that self-reported frequency of skill use at work does not necessarily relate to demonstrated proficiency of that skill. For example, from the quintile who reported the most frequent use of numeracy skills at work, 17% of U.S. adults scored at Level 1 or below and only 16% scored at the highest levels (Levels 4/5). Furthermore, 7% of those who reported the least frequent numeracy skill use at work (bottom quintile) scored in the top 10%. Across all countries, only a weak correlation was found between reported skill usage at work with either numeracy or reading ability (OECD, 2103a). Perhaps the weak relationship in actual skill with reported frequency of use may result from a self-report bias or that people are employed in occupations that are poorly matched with their skills. The following sections summarize results on the environmental factors. First-order factors are presented in decreasing order of their relationship to the second-order Environmental factor.

Numeracy at work. Although Americans lag in numeracy ability, U.S. participants reported the most frequent use of numeracy skills compared to all other countries (OECD, 2013a), which provides further evidence that reported skill use does not strongly correlate with actual ability. A majority of both groups in this study reported using most numeracy skills at work at more than one time per month. In the lower numeracy group, however, the majority never prepared graphs or charts or used simple algebra or formulas at work. The top 10% group was twice as likely to ever use math skills that are traditionally taught in high school and beyond (e.g., algebra, advanced math, and statistics). The three individual items most strongly related to the Numeracy at Work factor were preparation of graphs and charts, use of simple algebra, and use of advanced math/statistics.

Across all PIAAC participating countries, the type of job was a more important predictor of numeracy skill usage at work compared to actual numeracy ability. This underscores how numeracy skills can develop after the completion of terminal education, especially if one's occupation requires it (Carpentieri et al., 2010). Conversely, if not used in employment, numeracy skills decline (Bynner & Parsons, 1998; DfES, 2004).

Technology motivation at work. The majority of high performers and low performers reported daily computer use to collect work-related information. Although most people reported they never used programming language at work, the top 10% were almost 2 times more likely to ever use the skill as part of their employment. All four items comprising this factor were strongly related to the factor (λ^2s = .45 to .77). Over 77% of the variance in the Technology Motivation at Work factor was explained by the item that addressed computer use to collect work-related information.

Previous research suggests that individuals with good numeracy skills have greater access to computer technology and the internet (Parsons & Bynner, 2007). Women, according to the researchers, were more likely to use a computer at work compared to men, suggesting that computer skills are even more essential for women's employment. For those who had the lowest computer skills, DfES (2003) research found a strong correlation between digital technology skills and the lowest numeracy skills, possibly indicating a digital divide.

Reading at work. Reading skills are needed to apply mathematical understanding in everyday life. For example, Swain et al. (2008) asserted that numeracy skills should not be assessed in isolation because without literacy word problems would be very difficult to understand. In this study, a somewhat larger percentage of the highest numeracy group, compared to the lower numeracy group, read the following more than once a month: directions or instructions, newspapers or magazines, professional journals, or diagrams, maps, or schematics. The largest portion of the variance in the Reading at Work factor was explained by the item related to reading articles in professional journals or scholarly publications.

Job culture/problem solving. This factor included items related to planning and problem solving at work. The top 10% were more likely to plan their own activities and organize their own time on a daily basis compared to the group with lower skills. Both groups appeared similar on their frequency of solving simple problems. There was a moderate relationship between the factor and its four indicators.

Other research regarding job culture and problem-solving skill use at work is scant. U.S. PIAAC participants reported the most frequent use of problem-solving skills compared to all other countries (OECD, 2013a). The frequency of problem solving at work, on average, however, has been found to increase with the size of the employer (OECD, 2013a). However, the ability to organize one's own work is fairly even across sectors, meaning that agricultural and construction workers use self-organizing skills as frequently as those in finance and insurance. In the gifted adult research, gifted men, compared to gifted women, valued the ability to exercise leadership at work, and the freedom from supervision, to do what they wanted, and to do their job without interruptions.

Learning at work. This study demonstrated little, if any, difference in the reported frequency of Learning at Work indicators between high performers and lower performers. Similar to other measures of skill use, U.S. adults indicated more frequent use of learning at work skills compared to most other countries (OECD, 2013a). In the gifted literature, learning skill use at work is not something that typically researched but is hypothesized to be theoretically related. Among gifted men and women, there was no difference in their preference to learn new things at work, but men preferred a challenging job (Lubinksi et al., 2014). Of the three items comprising the factor, the item regarding keeping up to date with products or services had the strongest relationship with the Learning at Work factor.

Environmental Characteristics Summary

Although the Numeracy at Work factor had the strongest relationship to the second-order Environmental factor, it appeared all but one of the factors were moderately to strongly related to Environmental (λ^2s = .59 - .77). Learning at Work factor was the factor with the weakest relationship (λ^2 = .34).

As the path in our post hoc model from Environmental to Numeracy was not significant (and the confidence interval encompasses both positive and negative values), an effect of skill use at work and adult numeracy ability could not be supported. Although the potential impact of three environmental covariates on numeracy achievement appear to be consistent with the literature (e.g., terminal education, the number of books in the home at 16, and employment), their indirect effects are not substantiated. Of the covariates, terminal education had a moderate effect and books at home had a small effect on Environmental. Given the inconclusive relationship of the second-order Environmental factor to Numeracy, however, an indirect effect of those characteristics on numeracy achievement is not supported. No effect was found for the following characteristics when all other variables were held constant: having a non-native mother or father, mother's terminal education, or father's terminal education.

Intrapersonal Findings

Intrapersonal Background

Whereas environmental characteristics typically include people and institutions that are external to the individual, intrapersonal characteristics typically reflect biologically-influenced demographics and internally driven behaviors. Intrapersonal background characteristics such as gender, race as well as nonintellective characteristics such as learning motivation are included.

Gender. As expected, males outperformed females in numeracy ability. Males were almost twice as likely to be in the top 10% numeracy group compared to females. Slightly more males comprised the lower numeracy group, but even within the lower group, the average numeracy score for males was higher than the average female score. This is consistent with U.S. PIAAC results in which males outperform females within every age category and at every educational attainment level (U. S. Department of Education, 2018). On the international PIAAC numeracy assessment, 16% of males and 9% of females scored at the highest level compared to 12% of U.S. males and 6% of U.S. females (Goodman et al., 2013).

Males are also disproportionately represented in the STEM or mathematically-gifted adult literature. It is not surprising that the initial four SMPY cohorts, chosen on the basis of exceptional SAT scores, were predominantly males (Ferriman et al., 2009; Lubinski et al., 2001) as young men have scored significantly higher than females on the SAT-Mathematics test for over 50 years (Perry, 2018). In 2016, 80% more males (9.4%) compared to females (5.1%) scored at the top SAT range (700-800). Females, however, appeared more likely to respond to the 20-year and 40-year follow-up research, which increased the proportion of female representation from 32% to 39% (Benbow et al. 2000; Lubinski et al., 2014). To reduce the overrepresentation of males, the percentage of male and female Cohort 5 graduate students were purposefully equalized (Ferriman et al., 2009; Lubinski et al., 2001). Similarly, less than one-third of the science talent search finalists were females, and over 80% of the National Academy of Science members were male (Feist, 2006). Given the overwhelming consistency in the literature of males outperforming females at the highest levels on every standardized measure related to mathematics and the overrepresentation of men in STEM fields, it is not surprising that this study also demonstrated a gender effect. Females were less likely to be in the top 10% group compared to males.

Race. White individuals were overrepresented at the highest numeracy levels. Descriptive statistics for this study indicated White individuals were over 8 times more likely to be in the top 10% numeracy group compared to Black individuals and over 6 times more likely compared to Hispanic individuals. Given recent SAT-Mathematics performance, it appears race gaps may continue to persist, but these demographics may change. For example, although approximately 25% of college-bound Asian test-takers scored at the highest levels (between 700-800), only 6% of Whites, and less than 2% of Hispanics, and less than 1% of Blacks scored in that range (Reeves and Halikias, 2017).

White individuals are also disproportionately represented in the mathematically gifted adult literature. For example, all but one of the former-SMPY cohorts were over 85% Caucasian (Achter, Lubinski, & Benbow, 1996; Ferriman, 2008). After accounting for Asian individuals, the combined representation of Black, Hispanic and other races was 2% to 6%, depending on the cohort. Fortunately, the representation of non-European-American Science Talent Search participants has increased from 17% to 34% in 1995 (Feist, 2006).

Similar to gender, the research has consistently shown that, on average White individuals outperform Black and Hispanic individuals on mathematics or numeracy standardized tests. It was therefore surprising to find a very small effect for Black in this study, when all other variables are held constant. This finding indicates that one or more of the covariates such as gender, terminal education, learning disability, or books in the home account for all the variation between the races.

Age. Younger adults (age 25-34) were more likely to score at the highest numeracy levels compared to older adults and the youngest adults (age 16-14). In the lower numeracy group, the percentage of individuals was distributed more equally among age bands. The average numeracy score peaked for both groups between ages 25 to 34. Internationally, numeracy scores peak around age 30 and then gradually decline (OECD, 2016a; Paccagnella, 2016). U.S. adults, however, peak slightly later and have the smallest average decline from the peak to maturity compared to all other participating PIAAC countries (Paccagnella, 2016). Individuals who are the most proficient in numeracy, however, experience the least age-related decline (OECD, 2016a). U.S. adults, compared to the other nations, show the greatest differences between the numeracy scores of the top 10% and the bottom 10% of adults at age 45-65 reflecting increasingly different developmental trajectories. As the gifted adult literature typically selects a cohort in youth and follows the cohort to adulthood (longitudinal design), the literature does not report a comparison of abilities at different ages (cross-sectional design). The general age-related PIAAC numeracy ability curve, however, mirrors Desjardins and Warnke (2012) summary of research showing similar decreases in fluid intelligence over the lifespan (Paccagnella, 2016). On the PIAAC numeracy competency assessment, individuals in their 30s, on average, outperform younger and older adults. The results from the Adult Numeracy Achievement indicate a negative effect of age on Intrapersonal. In other words, for each 10-year age band increase the likelihood of scoring at the highest numeracy level is decreased.

Native language. Significantly fewer adults who took the PIAAC numeracy assessment in their non-native language scored in the top numeracy group compared to the percentage of non-native speakers in lower numeracy group (5% vs. 14%). According to OECD (2013a), foreign-born and/or non-English speaking adults are also disadvantaged with respect to the use of technology and information-processing skills in the United States. Additionally, non-native born individuals were also underrepresented in the top numeracy group with only 6% of adults born outside of the United States scoring at the highest levels (Goodman et al., 2013). Native language was not a characteristic reported in the gifted literature that was reviewed presumably because so few, if any, of the exceptional performers were non-native speakers.

Taking the numeracy measurement in a non-native language is a disadvantage for scoring in the top 10% group. The results from the SEM indicate a negative effect on the second-order Intrapersonal factor. Although one study with Australian youth, found no effects of non-native language on numeracy outcomes (Rothman and McMillan, 2003), this research was conducted in another culture and included only individuals who immigrated earlier than ninth grade.

Health. Highly numerate individuals were more likely to report very good to excellent health compared to less numerate individuals. Similarly, individuals in the top 10% of numeracy were 3 times less likely to report fair or poor health than the bottom 90^{th} percentile group. For individuals who lack basic numeracy skills, the likelihood of reporting poor health is substantially higher. One suggested reason for this health disparity is that because individuals with high numeracy skills can comprehend numerical health-related information more accurately they are able to make better health decisions (Reyna & Brainerd, 2007). In fact, the researchers argued that numeracy skills were crucial for making health judgments. Similarly, Prins, Monnat, Clymer, and Toso (2015) asserted that numeracy skills are a social determinant of health. Only one study of gifted adults included any health-related information. Over 78% of former Presidential Scholars in their late 50s/early 60s indicated they were satisfied to very satisfied with their health (Kaufmann & Matthews, 2012).

The results of this study are consistent with literature as well. There is an effect of health on Intrapersonal. Individuals who report better health are more likely to have a higher intrapersonal value.

Learning disability, vision or hearing difficulty. Individuals who reported a learning disability or who had difficulty seeing printed text were underrepresented in the top 10% numeracy group. Individuals with a learning disability or who had trouble seeing print (even with the help of contacts or glasses) were 2 times more likely to be in the low numeracy group. It is encouraging that some individuals (4%) with a learning disability demonstrated the capability of performing in the top numeracy group. Individuals with a learning disability in the less numerate group, however, scored significantly lower, on average, on the numeracy assessment. Carpentieri et al.'s (2010) review of numeracy literature reported that individuals with the lowest numeracy levels were 2.5 times more likely to report a disability or chronic illness. In one study, 36% of women and 56% of men with high dyslexic symptoms scored at the lowest levels (i.e., the standard expected to typically 7 to 9-year-olds) of numeracy (Bynner & Parsons, 2006). In addition, even when controlling for other factors, individuals at-risk for dyslexia were at greater risk for other outcomes: social engagement, political participation, employment in a job requiring computer skills, and achieving educational qualifications. A lack of research related to gifted adults with a learning disability (Rinn & Bishop, 2015) or vision difficulties prevents the addition of information from that field.

The results for vision difficulties and the presence of a learning disability are mixed. Although descriptive statistics indicated a difference between groups with respect to vision difficulties, no effect was found. A very small negative effect for learning disability on Intrapersonal was observed in this study.

Persistence. Persistence is examined through the lens of leaving school before completing a degree. The descriptive statistics showed no difference between the high numeracy group and the lower numeracy group in the percentage of individuals who left school before completing their educational program. Interestingly, when the covariates were combined, a small effect on Intrapersonal was found. In other words, those who discontinued a degree program or who were studying for a degree were more likely to have an increase Intrapersonal value.

Learning motivation. Participation in learning activities outside of a degree program was chosen to represent an individual's motivation to learn. Individuals in the top 10% group were significantly more likely to engage in training outside of a degree program. Over three-quarters of the high numeracy group reported taking courses compared to 55% of the below 90th percentile group. This is important because individuals differ in their willingness to pursue additional learning opportunities, which, in turn, may impact skill development (OECD, 2011). The results of the SEM indicate a positive effect on Intrapersonal for individuals who took courses outside of a degree program.

Summary. Given that the Adult Numeracy Achievement Model includes second-order factors, it is difficult to evaluate the indirect relationship of covariates on the categorical outcome (of numeracy achievement at the top 10% or not). Intrapersonal characteristics negatively related to the second-order factor, Intrapersonal, are female, the presence of a learning disability, age, and non-native language. Intrapersonal characteristics that are positively related to the second-order factor are taking courses outside of a degree program, health, as well as Black. The indirect relationship of the covariate through Intrapersonal to Numeracy should decrease in magnitude but remain the same in the direction of the effect.

Intrapersonal Factors – Skill Use at Home or in Everyday Life

In this study, behaviors and skills that are required and used in the workplace were considered to be environmental influences. Skills used in everyday life and at home are considered to be intrapersonal influences because individuals can choose how and if these skills are used. Accordingly, intrapersonal factors used in the SEM included the frequency of use of learning strategies, numeracy skills, and technical/computer skills in everyday life. The intrapersonal factors are presented in decreasing order of relationship with the second-order Intrapersonal factor.

Numeracy at home. The most notable differences in the frequency of numeracy skill use in everyday life were seen in the use of fractions, algebra, advanced math, and statistics. Perhaps these skills might require more problem solving or critical thinking. Literature from the gifted field suggests that intensive practice is positively associated with outcomes, and 10 years of practice or 10,000 hours is necessary to develop expertise (Ericsson & Charness, 1994; Ericsson, Krampe, & Tesch-Römer, 1993). Former Presidential Scholars retrospectively indicated that perseverance and hard work were essential (Kaufmann & Matthews, 2012). Former-SMPY participants reported the belief that hard work was necessary to develop their talents (Benbow et al., 2000). Similar to Numeracy at Work, the three individual items most strongly related to the Numeracy at Home factor in the SEM were preparation of graphs and charts, use of simple algebra, and use of advanced math/statistics.

Technology motivation at home. Although the use of a programming language was rarely reported in either group, twice as many in the top 10% reported programming in their everyday life compared to the below 90th percentile group. The percentage of individuals who used a spreadsheet in their everyday life was also twice as many in the top 10% group as in the lower skilled group. The two items that were most highly correlated with the Technology Motivation at Home factor were use of spreadsheets and use of programming language.

Learning approach. Almost all individuals reported using the various learning strategies at least some of the time. A greater percentage of the top 10% group, however, indicated that they tried to connect new ideas to real-life situations or to something they already knew. Personal strategies such as these may impact individuals' learning abilities and how easily they acquire skills. (OECD, 2011). The variance in the Learning Approach factor was best explained by the items related to enjoyment of learning new things and of figuring out how different ideas fit together.

Learning motivation. This factor was dropped in the post hoc model for several reasons. First, the indicators were measured on a different scale (yes/no) than the ordinal scale of all the other factor indicators. Second, multicollinearity appeared to be an issue with model fit. Third, a single item could be used as a covariate to capture the essence and would increase model parsimony. This decision is further supported because the single item was highly correlated with all the other items in the factor (see Table A.20).

Reading at home. The amount of time an individual engages in reading outside of work may also be an indication of investment in learning. Since a majority of both groups engaged in reading a variety of materials at least once a week, the variable did not appear to differentiate well between the groups. A slightly larger percentage of the high numeracy group read the following more than once a week: letters, memos, or mail; newspapers or magazines, books; and diagrams, maps, or schematics. This factor was dropped in the final post hoc model.

Intrapersonal Characteristics Summary

The Numeracy at Home factor ($\lambda^2 = .64$) and the Technical Motivation at Home ($\lambda^2 = .79$) factor had the strongest relationship to the second-order Intrapersonal factor. It appears that all but one of the factors were moderately to strongly related to intrapersonal ($\lambda^2 = .79$). The Learning Approach factor is only weakly related ($\lambda^2 = .23$). The Reading at Home factor was dropped in the post hoc model, and the Learning Motivation factor was replaced with a single item.

The interpretation of covariate effects on numeracy achievement is somewhat more straightforward given a positive effect ($\gamma = .33$) of Intrapersonal on Numeracy. Positive effects on the second-order intrapersonal factor will have an indirect positive effect on numeracy achievement and vice versa. In other words, increasing Intrapersonal values predicted membership in the top 10% group and decreasing Intrapersonal predicts membership in the lower numeracy group. Small positive indirect effects on numeracy achievement were taking courses outside of a degree program, health, as well as Black. The surprising indirect positive effect of being Black on numeracy suggests that the variance associated with the lower numeracy scores of Black individuals is accounted for by one or more other covariates such as terminal education, the presence of a learning disability, gender, or the number of books in childhood home. Negative effects on the second-order Intrapersonal factor, when holding all other items constant, are female, the presence of a learning disability, age, non-native language. No effect was found for difficulty seeing print.

Other Comments Regarding SEM Findings

The multicollinearity of PIAAC items and factors can be problematic. The high correlation between an individual's literacy and numeracy skill has been established; the U.S. adults have the second strongest correlation (.89) between proficiency in literacy and numeracy among all participating countries (OECD, 2013a). Two factors were dropped in the post hoc model largely because of multicollinearity problems.

Additionally, Intrapersonal and Environmental were also highly correlated. An explanation for this association might be that an enriched environmental background might cultivate better health, predict degree completion, and increase the likelihood of participation of learning activities. Conversely, specific intrapersonal characteristics might influence the expression of environmental facets. For example, perhaps cultivation of skills outside of work may influence skill use at work. It is possible that race, gender, and learning disability might influence one's employment, terminal education, opportunities to learn at work, use of skills at work, and job culture. Once the shared variance is accounted for in SEM, all that is left to predict numeracy is the variance that is not shared between the two second-order factors. This shared variance may be one reason for a small pseudo-R^2.

Finally, the pseudo-R^2 value for the Adult Numeracy Achievement model was small. Although this statistic is commonly thought of the amount of variance explained by the model, the Institute for Digital Research in Education (2019) suggested "interpreting this statistic with great caution" (n.p.) as it is not equivalent to the R^2 associated with OLS regression. Furthermore, Willett and Singer (1988) asserted that statistics other than the coefficient of determination (pseudo-R^2) such as estimates of β are more important. This position appears to be supported by Muthén & Muthén (2004) as well.

Limitations

As with any study, limitations should be considered. Limitations related to the research design are described first. Data for this study was not collected longitudinally but represents a cross-sectional snapshot in time. As the sample included a cross section of U.S. adults from ages 16 to 65, data cannot be used to inform current practices at today's schools. Results cannot be generalized to those who were not employed (either because they self-selected to not be in the labor market or could not find a job) given that the CFA and SEM only included participants who had been employed in the 12 months prior taking the survey. Nor can these findings be generalized to other countries beyond the United States.

Because a post hoc model was used, one might assert that the model no longer represents the underlying theory. As mentioned previously, the post hoc model had two fewer factors, five fewer items, and one additional covariate was added to replace one factor. It should be noted that there are practically an infinite number of items that could be chosen to represent a construct. Therefore, removing an item or two does not change the content validity. As one factor appeared to be redundant and the other was replaced by a single item, arguably the construct validity is essentially unchanged as well.

Prior research indicates many more characteristics that are associated with developing any talent such as numeracy skills; however, this study could not include many of these aspects because the data source was not unlimited. The survey did not collect data for other items that have been suggested to contribute to talent development, such as: intelligence, years of education, number of math classes taken, participation in accelerated math courses or extracurricular activities that may contribute to the development of numeracy, quality of schools attended, significant people/mentors, skills used at previous jobs, skills used at other periods of life, affinity for the domain, and perseverance. It should be noted, however, that large-scale empirical research with talented adults is very rare. The research that has been done typically follows youth that were identified in youth as having exceptionally high potential into adulthood and ignores those who did not meet the cutoff criteria in youth. Beyond identifying individuals based on adult performance, this study also investigated other or under-researched potential characteristics that could contribute to numeracy talent development such as employment, job culture, the use of numeracy skills at work, the use of numeracy skills in everyday life, and technology/computer skill use.

Although the selected dataset had a wealth of data, there are some other limitations associated with the PIAAC data. Limitations that specifically impacted this study were PIAAC-constructed scales that appear to need more stringent confirmatory analysis and missing data (as a result of skip patterns or for other reasons). A large amount of missing data prevented the inclusion of variables such as college major and annual income. Additionally, PIAAC numeracy items were not constructed to minimize bias; therefore differences might be attributed to differential item functioning rather than actual differences in race or ethnicity. Furthermore, as with any survey, all the demographic and skill use data were self-reported. Moreover, the administration of an adaptive instrument that does not provide one score was difficult for data analysis but allows for greater precision in a shorter testing period and should ultimately reduce error. Although the PIAAC has limitations, arguably, the expertise of the test designers, ease of access to large international samples, and weighting to provide population estimates more than make up for its limitations.

Researcher limitations also occurred. For example, although it was planned to complete a final SEM analysis in which the 80 replicate weights were applied to all 10 sets of plausible values, this was not possible because of time limitations and lack of computing resources. After running the analysis for over 24 hours, the computer software was only on the third replicate weight of the first set of plausible values and still had 797 iterations to complete. More powerful computers were also tried with only slight increases in speed. The application of replicate weights is suggested because of PIAAC's clustered sampling approach versus simple random sampling. Because the IDE was used to report descriptive statistics, replicate weights have been accounted for in the descriptive statistics, but they have not been applied to the SEM. Without the application of the replicate weights to the model, the population standard errors were not adjusted. It is, therefore, possible that with replication weights some of the loadings would no longer demonstrate statistical significance. This means that the potential of a type 1 error, or the rejection of a true null, is increased. In other words, we may have incorrectly assumed that a characteristic was significantly related to numeracy development, when in fact it was not. The range of standard errors listed in the descriptive tables (with replicate weights applied) was larger (0.1 to 7.8) than the range in the model results (.01 to .03). Even with larger standard errors found in the descriptive statistics, all of the between-groups two sample z-tests that were selected showed statistical significance. Furthermore, the model statistic *p*-values were typically either nonsignificant or zero. Therefore, it is unlikely that the application of replicate weights would significantly alter the conclusions.

Finally, two limitations are related to statistical considerations. First, the lack of model fit guidelines is a hindrance. Recommended fit statistics cutoff levels were made using models with only three factors. As there are not recommended fit statistics for large models or models with second-order factors, it is difficult to ascertain if the model fit is sufficient for drawing conclusions. Second, one of the main objectives was to compare the top 10% in numeracy with others. The proposed Adult Numeracy Achievement Model required a very large sample given the number of variables. Although there is no consensus, the suggested sample size for factor analysis ranges from 3 to 20 times the number of indicators (Mundfrom, Shaw, & Ke, 2005). It was necessary, therefore, to retain as many participants as possible. In light of this, it was decided to use a binary outcome to compare the 10% to the remaining bottom 90%. Some might argue that comparing more moderate performers with the highest performers might provide a better comparison group. It is possible that a more fine-grained approach would be helpful; however, sample size and power needs led us to favor using the entire employed sample for this initial analysis. It might also be suggested that there is little difference between a person at the 88th percentile and one at the 90th percentile. The top 10% cutoff criterion was chosen given the theoretical support in the gifted and talented literature. A fine-grained approach comparing two other groups is an area for future research, especially given that Parsons and Bynner (2007) noted the larger difference in adult outcomes between the U.K. national standards entry level 2 (expected standard of 7 to 9-year-olds) and entry level 3 (expected standard of 9 to 11-year-olds).

Future Research

Primary areas for research include methodological or statistical as well as further numeracy investigations. Given less than ideal model fit indices, one could hypothesize that PIAAC theoretical assumptions do not hold. Another explanation, however, could be limitations related to model construction or to measurement. Methodological research would benefit future PIAAC investigations as well other disciplines that utilize survey research. Numeracy related research is the second area ripe for further inquiry and investigation.

Methodological/Statistical Suggested Research

Although PIAAC-constructed scales have strong content validity given subject-matter expert group involvement, the construct validity of the factors is less robust. Although a type of non-traditional confirmatory analysis had been done on most of the PIAAC scales used (Allen et al., 2016), it may not have been sufficient which means the assertion of construct validity is less tenable. For example, given model fit indices and a higher than expected correlation between factors, it appears that predictors loaded across multiple first-order factors and second-order factors resulting in multicollinearity issues. It is, therefore, suggested that PIAAC factors be reexamined using a subset of the sample to conduct an exploratory factor analysis to assess how items cluster together followed by a confirmatory factor analysis using the remaining sample. Alternatively, a multitrait-multimethod analysis could be conducted. Factors with stronger convergent and discriminant validity allow researchers for fitting models and greater validity when interpreting data and drawing conclusions.

It may also be interesting to compare model results using PIAAC-constructed index scores in lieu of PIAAC-constructed factors. Factors were selected for this study for two reasons. First, by including the actual items, the data retains the richness. Second, it is not clear how index scores were calculated so the validity of these single scores cannot be ascertained. While these limitations remain, this analysis may shed light on the representativeness of the index scores if the model results are similar.

A lack of model fit guidelines for models with many factors and second-order factors is concerning. As mentioned previously, models with three first-order factors were used in developing model fit suggested cutoff values (Hu & Bentler, 1999; Yu, 2002). However, the number of factors is one of many aspects that will change the relationship to fit statistics, and some researchers to assert that the fit criteria are too conservative (Beauducel & Whittman, 2005; Brown, 2015). Yet, there is no agreement for specific cutoff values for models with significantly more factors or second-order factors.

A couple of findings may suggest that an alternative investigation using a single-level model may be worthwhile. First, the high correlation of Intrapersonal and Environmental second-order factors indicates that 42% of the variance is shared. This suggests that intrapersonal and environmental characteristics may not be as different as we originally thought and, as a result, non-shared variance is all that remains to predict numeracy. Second, given the ambiguous finding of the second-order Environmental factor, it is unclear how specific environmental factors or environmental covariates directly or indirectly impact numeracy achievement. In other words, although prior research and descriptive statistics suggest that an individual factor or a particular covariate has a positive or negative effect, but the effect is obscured by the combination of the predictors and covariates in the post hoc Adult Numeracy Achievement Model.

Finally, access to supercomputing power would be helpful for two other statistical items. First, final analysis with the application of replicate weights could not be conducted. It would, therefore, be useful for future researchers who are also limited by computing power to know how much change, if any, is found between analysis with and without the addition of replicate weights. Second, missing data is a problem in survey research, especially given that skip patterns automatically result in missing data. Statistical tests have been created with the assumption that data are missing at random and assume that the value of missing data are unknown. As skip patterns reflect underlying characteristics, however, the value is theoretically partially known (i.e., censored) data. Future research that would need supercomputing capabilities could investigate statistical procedures that could be applied to CFA and SEM if missing data was censored or resulting from skip patterns.

Numeracy-Related Research

As an initial investigation, this study was intentionally limited in scope. In addition to the suggestions listed above, a greater depth of understanding could be gained by expanding the breadth of research. For example, this study only examined U.S. participants, but this analysis could be extended to participants in one or more of the 33 countries that participated in the 2012 or the 2014 data collection. If statistical procedures were determined to treat missing data as censored data, then the study could be expanded to include individuals who were unemployed or out of the workforce. Furthermore, additional variables could be added to capture other characteristics or factors that may contribute to numeracy development. Finally, a lifespan perspective of numeracy development or cohort effect could be examined using multiple data sets. The PIAAC was intentionally created with similarities to previous international surveys including the Program for International Student Assessment (PISA; 2000 to present) with an adolescent sample and the Adult Literacy and Life Skills (ALL) Survey (2003 to present). The Survey of Adult Skills Reader's Companion (OECD, 2016) outlines variables that are shared between surveys.

Future research could also narrow the comparison group. Instead of comparing the top 10% to the remaining 90%, the top 10% (Level 4/5) could be compared to another group (e.g., Level 1, Level 3, or Levels 1 and 2).

Numeracy skills could also be examined using a different theoretical lens. OECD's (2011) model of skill acquisition and decline represents the primary elements that influence the acquisition and decline of skills, including education and training, personal background characteristics, and work characteristics (see Figure 5.2). Although there are significant overlap in the variables in the Adult Numeracy Achievement Model and OECD's model, a study could investigate which model fits the data better.

Summary and Implications

This chapter discussed the results and conclusions of the present study. As the initial Adult Numeracy Achievement Model was found to have an unacceptable model fit, a post hoc model of Adult Numeracy Achievement Model was proposed. Findings from the study confirmed the effect of intrapersonal factors and characteristics. Implications for future research related to methodological improvement were detailed including (a) the need for exploratory factor analysis, (b) updated fit recommendations for models with many factors or models with higher-order factors, (c) comparison of results when using PIAAC index scores versus factor scores, (d) comparison of single-level numeracy achievement model, (e) examination of differences with application of replicate weights, and (f) procedures to convert missing data resulting from skip patterns to censored data. Additional numeracy-related research was also suggested.

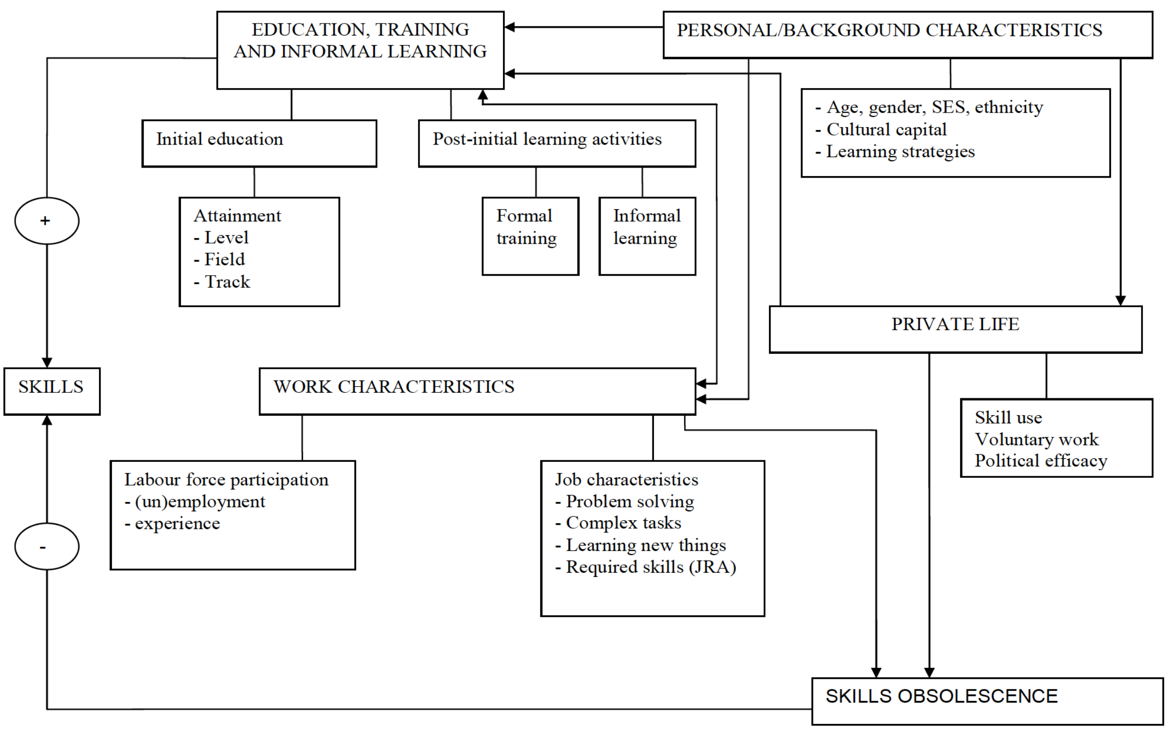

Figure 5.2. Schematic Representation of Skill Acquisition and Decline (OECD, 2011, p. 54)

In conclusion, practical applications for parents, educators, adults, and policymakers are suggested. First and foremost, popular beliefs regarding the development and necessity of numeracy skills need to change (Orwood & Brown, 2015). Without changes in beliefs, Orwood and Brown argue that the bold actions that are necessary to improve numeracy on an individual and national level are unlikely to happen.

Parents need to know that numeracy matters. Parents need to know that numeracy skills are positively associated with good health, employment, and educational attainment. Numeracy skills appear to matter in every occupation. Carnevale and Desrochers (2003) asserted "although the wage premium for college-educated workers has increased across all disciplines, it has increased primarily among those who participated in curricula with stronger mathematical content, irrespective of their occupation" (p. 22). Parents, therefore, should engage their children in applying mathematical principles in everyday life and encourage their children to take as many mathematics courses as possible. There is a strong correlation between literacy and numeracy and results from this study suggest that providing access to books in the home may also support numeracy development. Given the gender divide in numeracy, encouraging daughters may be even more important. Furthermore, parents and educators need to counter statements that infer mathematical understanding is innate (i.e., that a math gene exists) or that only some people are good at math. Instead, they need to adopt the belief that every person can become numerate and this skill is necessary for success in the 21st century (Orwood & Brown, 2015). Stevenson and Stigler (1994) suggest that Americans need to learn to adopt the perspective held by many Asian societies in which hard work and effort are key to mastery rather than focus on self-defeating beliefs such as innate ability.

Adults too need to improve numeracy skills and change their beliefs. According to this study, enhancing and utilizing technical skills and numeracy skills at home more frequently predicts higher numeracy. Increasing use of numeracy skills in everyday life such as preparing charts/graphs/tables or use of algebra, advanced math, and statistics appear to predict numeracy achievement. Likewise, using computers for things such as creating spreadsheets also seem to predict better numeracy. According to this study, participation in adult learning activities (outside of a degree program) also predicts higher numeracy, although this item may merely reflect a learning orientation.

Educators and politicians need to understand that both literacy and numeracy matter. Educators at all levels need to learn to infuse numeracy into the curriculum. Mathematical curriculum should emphasize practical application. Present and future educators need more numeracy development as part of teacher preparation programs and professional development. For example, American teachers had lower average numeracy scores compared to other U.S. college graduates and compared to teachers internationally (Hanushek, Piopiunik, & Widerhold, 2014). This should not be acceptable. In order to improve the numeracy levels of the nation, educators and politicians should require that students take more math classes to earn a high school diploma. Mathematical understanding can also become a requirement for more postsecondary degree programs. Although numeracy skills can develop in the workforce, the more proficient individuals are more likely to be in jobs that continue to maintain or develop skills. Therefore, it is imperative that all people leave school with strong numeracy skills (OECD, 2016a). Politicians need to follow the lead of other nations and push for continued numeracy research, especially in the field of adult professional development (Condelli et al., 2006).

Fortunately, reform prospects are bright given that market forces should drive increasing numeracy educational investments in light of expected economic returns (Carnevale & Desrochers, 2003). In conclusion, my research sheds light on characteristics of the highest performers, but as acting commissioner of National Center for Education Statistics said, “Clearly, we have some work to do in this country” (Anderson, 2016, n.p.).

APPENDIX

APPENDIX A

CFA of First Order Factor Results

This appendix presents the CFA findings for each first-order factor and provides correlations between items within each proposed factor. CFA, as compared to exploratory factor analysis, was chosen because subject matter expert groups developed the following PIAAC scales: Numeracy at Work, Reading at Work, Learning at Work, Technology/ Computer Skills at Work, Numeracy at Home, Reading at Home, Learning Approach, and Technology/Computer Skills at Work. OECD also reports the scales were confirmed sales using “reliability analyses and scale refinement as well as predictive analyses using a proxy of the respondent’s test score (the so-called ETS zlogit score)” (Allen et al., 2016, p. 3-30): The Job Culture and Learning Motivation scales were self-constructed. All PIAAC survey items selected for factor analysis were measured with Likert-type response options except for Learning Motivation items, which had categorical response options (e.g., yes/no). The indicator with the highest factor loading was selected to be the marker variable for each CFA (i.e., unstandardized value of 1.0) and is indicated with an asterisk. If model fit was not within acceptable ranges (e.g., CFI $\geq$ .95, RMSEA $\leq$ .06, SRMR $\leq$ .08, and TLI $\geq$ .95), then modification indices were examined. If conceptual or theoretical justification supported modification to the model to improve model fit, then changes were made and the new CFA was reported. The correlation tables present polychoric correlations results which compare ordered variables to ordered variables.

Numeracy at Work

Correlations for Numeracy at Work items ranged from .29 to .74 (see Table A.1). Standardized factor loadings (i.e., correlation between item and its factor) were .66 or higher, however, the standardized factor loading for G_Q03C was very high (see Table A.2). In this example, G_Q03C had a standardized factor loading of .89 indicating that 79% (i.e., $.89^2 = .79$) of the variance in the item was related to or explained by the factor. While high reliability in items is usually favorable, in this case, including G_Q03C led to issues with fit and issues with the loading of other items. Kenny (2016) indicated that as a rule of thumb, a correlation of .85 or higher may result in poor discriminant validity and multicollinearity issues. Later, G_Q03B was dropped because of high correlation with an indicator in reading at work that was preventing an interpretable model. Furthermore, two indicators were correlated given their conceptual similarity, high correlation of indicators, and modification indices: G_Q03G (use simple algebra or formulas) and G_Q03H (use advanced math or statistics). Table A.3 presents the CFA results for the factor structure that was used in the SEM.

Table A.1

Correlation/Covariance Table for Numeracy at Work Factor Items

Item	G_Q03B	G_Q03C	G_Q03D	G_Q03F	G_Q03G
G_Q03B					
G_Q03C	.65				
G_Q03D	.66	.77			
G_Q03F	.29	.50	.49		
G_Q03G	.34	.69	.59	.59	
G_Q03H	.26	.58	.48	.59	.74

Table A.2

Standardized and Unstandardized Coefficients for Numeracy at Work CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
G_Q03B	0.66	0.01	0.73	0.01
G_Q03C*	0.89	0.01	1.00	0.00
G_Q03D	0.84	0.01	0.94	0.01
G_Q03F	0.64	0.01	0.71	0.01
G_Q03G	0.79	0.01	0.89	0.01
G_Q03H	0.77	0.02	0.86	0.02

Note. Model Fit: $\chi 2(9) = 1132.61$, $p < .05$; RMSEA = .15; CFI = .95; TLI = .91; SRMR = .07.

Table A.3

Standardized and Unstandardized Coefficients for Numeracy at Work CFA Revised

Item	Std. λ	*SE*	UnStd. λ	*SE*
G_Q03D	0.68	0.01	0.81	0.02
G_Q03F	0.72	0.02	0.86	0.03
G_Q03G*	0.84	0.02	1.00	0.00
G_Q03H	0.79	0.02	0.94	0.02

Note. Correlated G_Q03G with G_Q03H. Model Fit: $\chi 2\ (1) = 22.1$, $p < .05$; RMSEA = .06; CFI = .99; TLI = .99; SRMR = .01.

Reading at Work

Correlations for Reading at Work items ranged from .29 to .79 (see Table A.4). Standardized factor loadings (i.e., correlation between item and its factor) were .47 or higher, however, the standardized factor loading for G_Q01D was very high (see Table A.5). In this example, G_Q01D had a standardized factor loading of .87 indicating that 76% (i.e., $.87^2 = .76$) of the variance in the indicator was explained by the factor which may result in poor discriminant validity and multicollinearity issues. Items G_Q01G and G_Q01H were dropped because of their lower loadings. Other indicators that were highlighted by modification indices that had conceptual similarity and high correlation between the two indicators were correlated: G_Q01A (read directions) with G_01F (read manuals) and G_Q01C (read newspapers) and G_Q01D (read professional journals). Once these changes were incorporated, G_Q01B had a high factor loading and was, therefore, dropped. Table A.7 presents the CFA results for the factor structure that was used in the SEM.

Table A.4

Correlation/Covariance Table for Reading at Work Factor Items

Item	G_Q01A	G_Q01B	G_Q01C	G_Q01D	G_Q01E	G_Q01F	G_Q01G
G_Q01A							
G_Q01B	.49						
G_Q01C	.39	.70					
G_Q01D	.38	.68	.79				
G_Q01E	.34	.45	.52	.55			
G_Q01F	.59	.50	.45	.48	.44		
G_Q01G	.19	.51	.40	.37	.19	.26	
G_Q01H	.44	.41	.37	.40	.33	.53	.33

Table A.5

Standardized and Unstandardized Coefficients for Reading at Work CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
G_Q01A	0.61	0.01	0.71	0.02
G_Q01B	0.80	0.01	0.93	0.01
G_Q01C	0.85	0.01	0.99	0.01
G_Q01D*	0.87	0.01	1.00	0.00
G_Q01E	0.60	0.01	0.70	0.02
G_Q01F	0.68	0.01	0.79	0.01
G_Q01G	0.47	0.02	0.54	0.02
G_Q01H	0.57	0.01	0.66	0.02

Note. Model Fit Statistics: $\chi 2$ (20)=1573.62, $p < .05$; RMSEA = .12; CFI = .94; TLI = .92; SRMR = .05.

Table A.6

Standardized and Unstandardized Coefficients for Reading at Work CFA Revised

Item	Std. λ	*SE*	UnStd. λ	*SE*
G_Q01A	0.50	0.02	0.65	0.03
G_Q01C	0.74	0.01	0.95	0.02
G_Q01D*	0.78	0.01	1.00	0.00
G_Q01E	0.71	0.01	0.91	0.03
G_Q01F	0.62	0.01	0.80	0.03

Note. Dropped G_Q01B, G_Q01G and G_Q01H. Correlated G_Q01A with G_Q01F and G_Q01C with G_Q01D. Model Fit Statistics: $\chi2$ (3) =10.51, $p < .05$; RMSEA = .02; CFI = 1.00; TLI = .1.00; SRMR = .01.

Technical/Computer Skill Use at Work

Correlations for Technical/Computer Skill Use at Work items ranged from .35 to .71 (see Table A.7). Standardized factor loadings were .58 or higher, however, the standardized factor loading for G_Q05C was very high (see Table A.8). In this example, G_Q05C had a standardized factor loading of .95 indicating that 90% (i.e., $.95^2 = .90$) of the variance in the indicator was explained by the factor which results in poor discriminant validity and multicollinearity issues. Model fit statistics this factor, however, are all within acceptable levels so the factor was retained.

Table A.7

Correlation/Covariance Table for Technical/Computer Skill Use at Work Factor Items

Item	G_Q05C	G_Q05D	G_Q05E
G_Q05C			
G_Q05D	.71		
G_Q05E	.75	.57	
G_Q05G	.52	.35	.54

Table A.8

Standardized and Unstandardized Coefficients for Technical Skill at Work CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
G_Q05C*	0.95	0.01	1.00	0.00
G_Q05D	0.73	0.01	0.77	0.02
G_Q05E	0.80	0.01	0.84	0.02
G_Q05G	0.58	0.02	0.61	0.02

Note. Model Fit Statistics: $\chi 2$ (2) =35.38, $p < .05$; RMSEA = .05; CFI = .99; TLI = .99; SRMR = .02.

Learning at Work

Correlations for Learning Work items ranged from .36 to .47 (see Table A.9). Standardized factor loadings were .59 to .76 (see Table A.10). Model fit statistics for the latent variable Learning at Work indicate that the CFA model was just identified, meaning that the number of free parameters was the same as the estimated parameters (i.e., zero degrees of freedom). Although this would be problematic if there were only one factor, Learning at Work was only one of many factors that was part of a SEM; in the full model degrees of freedom were borrowed from other first-order factors.

Table A.9

Correlation/Covariance Table for Learning at Work Factor Items

Item	D_Q13A	D_Q13B
D_Q13A		
D_Q13B	.47	
D_Q13C	.36	.45

Table A.10

Standardized and Unstandardized Coefficients for Learning at Work CFA

Item	Std λ	*SE*	UnStd. λ	*SE*
D_Q13A	0.61	0.02	0.81	0.04
D_Q13B*	0.76	0.02	1.00	0.00
D_Q13C	0.59	0.02	0.78	0.03

Note. Model Fit Statistics: $\chi2$ (0) = 0; RMSEA = .00; CFI = 1.00; TLI = 1.00; SRMR = .00.

Job Culture

Correlations for Job Culture indicators ranged from .36 to .80 (see Table A.11). Standardized factor loadings were .44 to .93 (see Table A.12). Even though F_Q05B had a lower factor loading, the item was kept in order to keep at least one degree of freedom. Given the conceptual similarity of F_Q03A (planning own activities) with F_Q03C (organizing own time), these two items were correlated to improve model fit (see Table A.13).

Table A.11

Correlation/Covariance Table for Job Culture Factor Items

Item	F_Q03A	F_Q03B	F_Q03C
F_Q03A			
F_Q03B	.61		
F_Q03C	.80	.53	
F_Q05B	.36	.37	.36

Table A.12

Standardized and Unstandardized Coefficients for Job Culture CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
F_Q03A*	0.93	0.02	1.00	0.00
F_Q03B	0.66	0.02	0.72	0.02
F_Q03C	0.85	0.02	0.92	0.02
F_Q05B	0.44	0.02	0.47	0.02

Note. Model Fit Statistics: $\chi 2$ (2) =75.20, $p < .05$; RMSEA = .08; CFI = .99; TLI = .98; SRMR = .02.

Table A.13

Standardized and Unstandardized Coefficients for Job Culture CFA Revised

Item	Std. λ	*SE*	UnStd. λ	*SE*
F_Q03A*	0.79	0.02	1.00	0.00
F_Q03B	0.77	0.02	0.98	0.04
F_Q03C	0.71	0.02	0.90	0.02
F_Q05B	0.48	0.02	0.61	0.03

Note. Correlated F_Q03A with F_Q03C. Model Fit Statistics: $\chi 2$ (1) =12.04, $p < .05$; RMSEA = .04; CFI = 1.00; TLI = .99; SRMR = .01.

Intrapersonal Factors

Numeracy at Home

Correlations for Numeracy at Home items ranged from .22 to .78 (see Table A.14). Standardized factor loadings were .57 to .84 (see Table A.15). Although the standardized factor loading for H_Q03C (.83) and H_Q03H were high (.84), once indicators were correlated those factor loadings decreased and the resulting model fit was improved (see Table A.16). Similar to Numeracy at Work, conceptually calculating prices, costs and budgets (H_Q03B) correlates with using decimals and percentages (H_Q03C) as does the use of algebra/formulas (H_Q03G) with using advanced math/statistics (H_Q03H). Use of decimals and percentages (H_Q03C) correlates with the use of a calculator (H_Q03D). Finally, calculating prices (H_Q03B) also correlates with the use of a calculator (H_Q03D).

Table A.14

Correlation/Covariance Table for Numeracy at Home Factor Items

Item	H_Q03B	H_Q03C	H_Q03D	H_Q03F	H_Q03G
H_Q03B					
H_Q03C	.59				
H_Q03D	.45	.58			
H_Q03F	.26	.51	.46		
H_Q03G	.31	.63	.46	.62	
H_Q03H	.22	.56	.45	.66	.78

Table A.15

Standardized and Unstandardized Coefficients for Numeracy at Home CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
H_Q03B	0.57	0.01	0.68	0.02
H_Q03C	0.83	0.01	0.99	0.02
H_Q03D	0.66	0.01	0.79	0.02
H_Q03F	0.71	0.01	0.85	0.02
H_Q03G	0.81	0.01	0.97	0.02
H_Q03H*	0.84	0.01	1.00	0.00

Note. Model Fit Statistics: $\chi 2$ (9) = 1307.94, $p < .05$; RMSEA = .16; CFI = .92; TLI = .87; SRMR = .07.

Table A.16

Standardized and Unstandardized Coefficients for Numeracy at Home CFA Revised

Item	Std. λ	*SE*	UnStd. λ	*SE*
H_Q03B	0.33	0.02	0.39	0.02
H_Q03C	0.71	0.01	0.83	0.02
H_Q03D	0.56	0.01	0.65	0.02
H_Q03F*	0.76	0.01	0.89	0.02
H_Q03G	0.86	0.01	1.00	0.00
H_Q03H	0.82	0.02	0.96	0.02

Note. Correlated H_Q03B with H_Q03C; H_Q03B with H_Q03D; H_Q03C with H_Q03D; and H_Q03G with H_Q03H. Model Fit Statistics: $\chi 2$ (5) = 88.11, $p < .05$; RMSEA = .05; CFI = 1.00; TLI = .99; SRMR = .01.

Technical/Computer Skill Use at Home

Correlations for Technical/Computer Skill Use at Home items ranged from .33 to .73 (see Table A.17). Standardized factor loadings were .58 or higher, (see Table A.18). The standardized factor loading for H_Q05C, however, was .87 indicating that 90% (i.e., $.87^2 = .76$) of the variance in the indicator was explained by the factor. Once H_Q05C and H_Q05D were correlated because of internet usage, the new model fit the data as indicated by model fit statistics within acceptable levels. (see Table A.19).

Table A.17

Correlation/Covariance Table for Technical/Computer Skill Use at Home Factor Items

Item	H_Q05C	H_Q05D	H_Q05E
H_Q05C			
H_Q05D	.73		
H_Q05E	.54	.52	
H_Q05G	.41	.33	.55

Table A.18

Standardized and Unstandardized Coefficients for Technical Skill Use at Home CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
H_Q05C*	0.87	0.01	1.00	0.00
H_Q05D	0.82	0.01	0.95	0.02
H_Q05E	0.65	0.01	0.75	0.02
H_Q05G	0.58	0.02	0.67	0.03

Note. Model Fit Statistics: $\chi 2(2) = 116.16$, $p < .05$; RMSEA = .10; CFI = .99; TLI = .96; SRMR = .05.

Table A.19

Standardized and Unstandardized Coefficients for Technical Skill at Home CFA Revised

Item	Std. λ	*SE*	UnStd. λ	*SE*
H_Q05C	0.61	0.03	0.61	0.03
H_Q05D	0.58	0.03	0.58	0.03
H_Q05E*	0.89	0.03	0.89	0.03
H_Q05G	0.62	0.03	0.62	0.03

Note. Correlated H_Q05C with H_Q05D. Model Fit Statistics: $\chi 2\ (1) = 5.93$, $p < .05$; RMSEA = .03; CFI = .99; TLI = .99; SRMR = .01.

Learning Motivation

Given binary data, tetrachoric correlations are provided for the Learning Motivation factor indicators (see Table A.20). Correlations for Learning Motivation items ranged from -.29 to .99 (see Table A.20). Given the very high correlation between B_Q12A_T and all the other variables (.83 to .99), the factor could be substituted with item B_Q12A_T. After dropping B_Q12A_T to prevent severe multicollinearity issues, I experimented with dropping one of the two other items with low loadings (B_Q02A and B_Q12G), but found that dropping B_Q02A resulted in a much better model fit. B_Q02A was dropped because of a low factor loading (-.29; see Table A. 20) and because of extremely low correlations with all the other items (-.05 to -.29; see Table A. 21). Model fit statistics of the revised Learning Motivation factor were all within acceptable levels (see Table A.22).

Table A.20

Tetrachoric Correlation Table for Learning Motivation Factor Items

Item	B_Q12A	B_Q12C	B_Q12E	B_Q12G	B_Q12A_T
B_Q12A					
B_Q12C	.37				
B_Q12E	.44	.48			
B_Q12G	.15	.04	.15		
B_Q12A_T	.91	.99	.97	.83	
B_Q02A	-.29	-.05	-.08	-.12	-.18

Table A.21

Standardized and Unstandardized Coefficients for Learning Motivation CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
B_Q12E*	0.74	0.03	1.00	0.00
B_Q12A	0.62	0.03	0.84	0.06
B_Q12C	0.62	0.03	0.84	0.06
B_Q12G	0.19	0.04	0.25	0.05
B_Q02A	-0.21	0.03	-0.28	0.05

Note. Dropped B_Q12A_T. Model Fit Statistics: $\chi2$ (5) =64.62, $p < .05$; RMSEA = .05; CFI = .94; TLI = .89; SRMR = .05.

Table A.22

Standardized and Unstandardized Coefficients for Learning Motivation CFA Revised

Item	Std. λ	*SE*	UnStd. λ	*SE*
B_Q12A	0.58	0.03	0.76	0.06
B_Q12C	0.63	0.03	0.82	0.07
B_Q12E*	0.77	0.03	1.00	0.00
B_Q12G	0.17	0.04	0.23	0.05

Note. Dropped D_Q12A_T and B_Q02A. Model Fit Statistics: $\chi2$ (2) = 7.84, $p < .05$; RMSEA = .02; CFI = .99; TLI = .98 SRMR = .02.

Learning Approach

Correlations for Learning Approach items ranged from .43 to .72 (see Table A.23). Standardized factor loadings were .71 to .83 (see Table A.24). The standardized factor loading for I_Q04L was fairly high (.83), however, after adding correlations between I_Q04J (i.e., getting to the bottom of different things) with I_Q04L (i.e., figuring out how different ideas fit together) as well as I_Q04B (i.e., relating ideas to real-life situations) with I_Q04H (i.e., relating information to things I already know), model fit statistics, except for RMSEA, were all within acceptable levels (see Table A.25).

Table A.23

Correlation/Covariance Table for Learning Approach Factor Items

Item	I_Q04B	I_Q04D	I_Q04H	I_Q04J	I_Q04L
I_Q04B					
I_Q04D	.57				
I_Q04H	.67	.63			
I_Q04J	.44	.56	.53		
I_Q04L	.54	.60	.60	.72	
I_Q04M	.43	.59	.49	.59	.60

Table A.24

Standardized and Unstandardized Coefficients for Learning Approach CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
I_Q04B	0.72	0.01	0.87	0.01
I_Q04D	0.77	0.01	0.93	0.01
I_Q04H	0.79	0.01	0.95	0.01
I_Q04J	0.78	0.01	0.94	0.01
I_Q04L*	0.83	0.01	1.00	0.00
I_Q04M	0.71	0.01	0.85	0.01

Note. Model Fit Statistics: $\chi 2(9) = 997.95$, $p < .05$; RMSEA = .14; CFI = .96; TLI = .93; SRMR = .04.

Table A.25

Standardized and Unstandardized Coefficients for Learning Approach CFA Revised

Item	Std. λ	*SE*	UnStd. λ	*SE*
I_Q04B	0.66	0.01	0.82	0.02
I_Q04D*	0.81	0.01	1.00	0.00
I_Q04H	0.74	0.01	0.92	0.01
I_Q04J	0.73	0.01	0.90	0.02
I_Q04L	0.79	0.01	0.98	0.01
I_Q04M	0.73	0.01	0.91	0.01

Note. Correlated I_Q04J with I_Q04L and I_Q04B with I_Q04H. Model Fit Statistics: $\chi 2$ (10)=246.43, $p < .05$; RMSEA = .08; CFI = .99; TLI = .98; SRMR = .02.

Reading at Home

Correlations for Reading at Home items ranged from .14 to .54 (see Table A.26). Standardized factor loadings were .37 to .71 (see Table A.27). Similar to the Reading at Work factor, multiple sets of indicators highlighted by modification indices were correlated because of their conceptual similarity: H_Q01A (read directions) with H_01F (read manuals), H_Q01D (read professional journals) with H_01F (read manuals), H_Q01G (read financial statements) with H_Q01H (read schematics), and H_Q01F (read manuals) with H_Q01H (read schematics). Table A.28 presents the CFA results after correlating the indicators as described; model fit statistics are all within acceptable levels.

Table A.26

Correlation/Covariance Table for Reading at Home Factor Items

Item	H_Q01A	H_Q01B	H_Q01C	H_Q01D	H_Q01E	H_Q01F	H_Q01G
H_Q01B	.45						
H_Q01C	.34	.54					
H_Q01D	.38	.44	.50				
H_Q01E	.30	.40	.35	.32			
H_Q01F	.48	.35	.31	.50	.33		
H_Q01G	.24	.34	.30	.19	.14	.21	
H_Q01H	.36	.35	.30	.42	.25	.50	.22

Table A.27

Standardized and Unstandardized Coefficients for Reading at Home CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
H_Q01B*	0.71	0.01	1.00	0.00
H_Q01A	0.61	0.01	0.87	0.02
H_Q01C	0.64	0.01	0.90	0.02
H_Q01D	0.69	0.01	0.97	0.02
H_Q01E	0.49	0.02	0.69	0.02
H_Q01F	0.69	0.01	0.98	0.02
H_Q01G	0.37	0.02	0.53	0.02
H_Q01H	0.60	0.01	0.85	0.02

Note. Model Fit Statistics: $\chi 2$ (2) = 644.23, $p < .05$; RMSEA = .07; CFI = .94; TLI = .92; SRMR = .04.

Table A.28

Standardized and Unstandardized Coefficients for Reading at Home CFA

Item	Std. λ	*SE*	UnStd. λ	*SE*
H_Q01A	0.58	0.01	0.78	0.02
H_Q01B*	0.74	0.01	1.00	0.00
H_Q01C	0.68	0.01	0.91	0.02
H_Q01D	0.67	0.01	0.90	0.02
H_Q01E	0.51	0.02	0.69	0.02
H_Q01F	0.51	0.02	0.69	0.02
H_Q01G	0.39	0.02	0.52	0.02
H_Q01H	0.54	0.02	0.73	0.02

Note. Correlated H_Q01A with H_Q01F; H_Q01F with H_Q01H; H_Q01D with H_Q01F; and H_Q01G with H_Q01H. Model Fit Statistics: $\chi2$ (17)= 281.73, $p < .05$; RMSEA = .05; CFI = .98; TLI = .96; SRMR = .03.

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