2018

The Influence of Quality of Education on a Regression-Based Method of Premorbid Estimated Intelligence

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THE INFLUENCE OF QUALITY OF EDUCATION ON A REGRESSION-BASED METHOD OF PREMORBID ESTIMATED INTELLIGENCE

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Submitted in Partial Fulfillment of the Requirements for the Degree of

Doctor of Psychology

May 2018

PHILADELPHIA COLLEGE OF OSTEOPATHIC MEDICINE
DEPARTMENT OF PSYCHOLOGY

Dissertation Approval

This is to certify that the thesis presented to us by Elizabet Santana

on the 8th day of May, 2018, in partial fulfillment of the requirements for the degree of Doctor of Psychology, has been examined and is acceptable in both scholarship and literary quality.

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Acknowledgements

I would like to thank the Kessler Foundation Neuroscience and Neuropsychology Lab for providing me with some of my most valued research experience, and for serving as the inspiration for this study. I would like to thank my chair, Dr. Stephen Poteau, for his dedication and commitment to this research project. I would also like to thank the other members of my committee, Dr. Donald Masey and Dr. Glenn Wylie, for their commitment, time, and feedback throughout the process.

This project would not have been possible without the support and patience of my friends and family. Thank you for empowering me to be and do my best.

Last, but certainly not least, I would especially like to thank my amazing husband, Philip. Thank you for always helping me reach my goals, and for your enduring support every time I make new ones, no matter how crazy they may seem. I love our life together.

Abstract

The physical, cognitive, behavioral, and emotional sequelae of brain injury have been shown to exert a substantial negative impact on everyday work-related and social functioning. Accordingly, accurate measurement of any associated cognitive decline is of paramount importance, and clinicians often face the challenge of estimating the patient's level of intellectual functioning prior to the brain pathology. This study examined the influence of environmental factors, such as education quality on a demographically based formula for estimating premorbid intelligence and focused primarily on an adjusted variable (reading level vs. years of education). The results showed that for the entire sample of the non-brain injured and the brain injured participants, only one of the variables used in the original Barona formula approached significance in predicting WASI FSIQ: gender. After adding the quality of education variable, the fit of the regression model significantly improved by 18%.

Surprisingly, when separating the clinical and non-clinical sample, the regression variables did not perform as well as expected. For the non-brain injured control sample, the improvement of the model only approached significance after including reading score. In contrast, results for the TBI sample indicated a significant improvement. Further, variables such as percentage of minorities in a school, school location's poverty level and educational quality were found to be closely associated. Future research should continue to identify environmental factors that might influence scores on measures of premorbid intelligence for a more individually tailored approach to diagnosis and treatment.

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Chapter 1: Introduction

Statement of the Problem

Traumatic brain injury (TBI) is a major public-health concern, with approximately 2.2 million individuals affected each year in the United States alone (Centers for Disease Control, 2015). Research has shown that brain injury can cause a range of cognitive impairments. Such impairments have been shown to exert a substantial negative impact on everyday functioning, including work-related and social functioning (Hart et al., 2004; Mazaux, 1997). The impact of TBI may be particularly salient for ethnic minority groups because of the 2.2 million reported incidences of TBI a year, more than half of the individuals are ethnic minorities (Centers for Disease Control, 2010). Moreover, numerous studies have found an association between racial minority status and poor post-injury outcomes after TBI (Arango-Lasprilla, Ketchum, Willaims, Kreutzer, & Marquez de la Planta, 2008; Gary, Arango-Lasprilla, & Stevens, 2009).

In an effort to assess cognitive deficits after a brain injury, clinicians use neuropsychological assessments to objectively quantify the severity of impairments and provide a profile of relative strengths and weaknesses that may be helpful in creating a personalized treatment plan (American Psychological Association [APA], 2001). In some cases, neuropsychologists are able to detect if there are any significant declines in cognitive functioning after a brain injury by comparing the patient's pre and post injury intelligence tests scores (Franzen, Burgess, & Smith-Seemiller, 1997; Green, Melo, Christensen, Ngo, & Monette, 2008). However, although ideal, these baseline tests scores are not often available. Consequently, clinicians often face the challenge of estimating the patient's level of intellectual functioning prior to the brain pathology (Franzen, et al., 1997; Green et al., 2008).

A common alternate approach to estimating pre-morbid IQ is using regression equations. Regression equations, such as the Barona method, which is based on the patient's age, sex, race, education and occupation, are often used to estimate the patient's baseline level of functioning prior to any brain pathology (Green et al., 2008; Klesges, Sanches, & Stanton, 1981). The results from this IQ estimate are utilized to interpret psychometric findings; scores on neuropsychological measures that are considerably lower than estimated intellectual capacity are typically interpreted as lower than expected, and possibly indicative of cognitive decline secondary to a neurological brain pathology.

Despite the benefits of using regression equations to estimate premorbid intelligence, these equations function under the assumption that years of education have the same implication across all individuals, regardless of differences in the quality of education. This truncated view ignores the possibility that, perhaps, for some individuals that experienced lower quality of education, the generated premorbid IQ derived from regression equations may be an overestimate; this places some patients at a higher risk for being misdiagnosed with a cognitive decline. The ramification of being misdiagnosed could perhaps lead to unnecessary treatment, financial losses and emotional distress (Strauss, Shermon & Spreed). Further, the misdiagnosis may negatively impact overall quality of life and induce negative self-appraisals (Strauss, Shermon & Spreed, 2006; Simpson, Mohr, & Redman, 2009). Individuals that are diagnosed with a cognitive impairment bear the consequences associated with the stereotypes and stigma of the diagnosis. It is well known that negative associations are often activated with diagnostic labels related to cognitive impairment and are damaging for the patient's social relationships and sense of self (Garand, Lingler, O. Conner, & Dew, 2009). In fact, Simpson et al. found that a diagnosis of brain injury activated feelings of shame and stigma in a group of patients from Italian, Lebanese and Vietnamese backgrounds (2009). For this group, cultural views appeared to be the main culprit in the connotations of stigma, to the degree that brain injury was perceived to be associated with madness (Simpson, Mohr, & Redman, 2009). Consequently, patients and their families reported isolating themselves from social groups in the attempt to minimize shame imparted both by self and others (Simpson, Mohr, & Redman, 2009). Similarly, individuals diagnosed with mild cognitive impairment or dementia have also been found to experience powerful stigmas and misconceptions associated with bearing such diagnostic labels, leading to diminished social interactions (Batsch & Mittelman, 2012).

Historically, group differences in IQ between African Americans and Caucasians have been well documented (Valencia & Suzuki, 2001). However, these racial disparities in cognitive testing are complex, with inherent underlying confounding factors. For instance, a disproportionate number of racial minority students are poor and perform at lower levels in school than middle-class students, primarily due to social class differences and a shortage of educational resources (Rothstein, 2004). Thus, over the years, research has shifted toward exploring social inequalities in educational experiences as, perhaps, the main culprit in explaining these achievement gaps (Dotson, Kitner-Triolo, Evans, & Zonderman, 2009; Condron, 2009). For instance, research has shown that regardless of race, individuals in high-income areas have greater access to a higher quality of education than individuals from low-income areas (Farah, Shera, Savage, Betancourt, & Gianetta, 2006; Noble, McCandliss, Farah, 2008). The impact of unequal education may, however, be particularly more salient for minorities, given the fact that they live in most of the low-income areas in the U.S (Jiang, Ekono, & Skinner, 2013). In fact, according to a recent analysis from the U.S government and accountability office, over time there has been a large increase in the percentage of public schools in the United States with students that are poor and predominantly Black and Hispanic (2016). Moreover, this recent report found that these racially and economically concentrated schools offer fewer resources and disproportionately fewer math, science and college prep courses, compared with other schools (U.S GAO, 2016). These differences in educational quality are, perhaps, driving the well-known relationship between racial classification and cognitive test performances. Therefore, measures that rely on the number of years of education without accounting for educational quality may be less accurate in measuring cognitive ability.

For this reason, a number of recent studies are suggesting that reading level may be a better predictor of overall cognitive abilities than reported years of education because it is able to capture an individual's quality of education (Manly et al., 2002; Manly et al., 1999). In fact, some studies have suggested that reading level predicts cognitive ability better than reported years of education (Byrd, Jacobs Hilton, & Manly, 2005; Johnson, Flicker, & Lichtenberg, 2006; Manly, Jacobs, & Touradji, 2002). For example, Dotsen et al. found that reading level, rather than years of education predicted performance on cognitive tests in a sample of African Americans who were predominantly of low SES (2008). These results may be explained by the fact that aspects of educational quality, such as teaching methods, teacher-pupil ratios, and accessibility to resources are not reflected in the number of years of education. On the other hand, the association between reading level and quality of education has been well-documented (Hedges, Laine, & Greenwald, 1994; Manly, Jacobs, & Touradji, 2002). Thus, many researchers agree that reading level may be a superior indicator of the knowledge and abilities obtained throughout formal schooling than the reported years of education (Ryan, Baird, Mindt, Byrd, Monzones & Morgello, 2005; Manly, Jacobs, & Touradji, 2002). Moreover, word-reading tests have been shown to be an effective measure of cognitive ability after a brain injury and are widely used by clinicians (Nelson & O'Connell, 1978). These tests have proven to be clinically useful in the brain injured population primarily because they are based on the premises that (1) reading ability has been shown to be a relatively preserved cognitive function in acquired brain injury, and (2) reading level is able to capture previous knowledge while reducing the demands on current cognitive abilities (Franzen, Burgess, & Smith-Seemiller, 1997).

To date, despite the rapid increase in racial and socioeconomic diversity among patients with head injuries, research examining the impact of unequal educational quality on standardized regression equations of premorbid cognitive ability is lacking for the population with TBI. Therefore, further exploration of the unique influences of quality of education on measures of premorbid IQ is essential for distinguishing pre- and post-cognitive ability after brain injury.

Purpose of the Study

The purpose of this retrospective study is to analyze the influence of quality of education on a regression equation of premorbid IQ. Specifically, it will extend the previous line of research on education quality, by exploring whether or not an adjusted regression equation, including a new education variable (reading level), could capture quality of education and therefore, better predict performance on premorbid estimates of intelligence on a healthy sample and on a clinical sample of TBI subjects. This study will initially aim to explore the predictive strength of the reading level variable, as compared with the years of education variable on the Barona equation. The existing dataset was originally collected to investigate cognitive fatigue and apathy in individuals who had sustained a brain injury (and in healthy controls). The study used a broad range of neuropsychological measures to assess verbal and nonverbal learning intelligence variables, including a commonly used reading level test. Additionally, a sociodemographic self-report measure was used to measure environmental social factors.

Chapter 2: Literature Review

Traumatic brain injury (TBI) is common in the United States, with approximately 2.2 million emergency department visits resulting from the injury each year (Centers for Disease Control, 2015 [CDC]; Langlois, Rutland-Brown, & Thomas, 2006). These numbers may be an underrepresentation of yearly injuries because many remain untreated (CDC, 2015). For instance, current reports indicate that an average of 3.2 to 5.3 million individuals in the United States are living with a TBI-related disability (CDC, 2015). TBI often results from an external mechanical force causing damage to brain tissue. The severity of a TBI (mild, moderate, severe) is based on Glasgow Coma Scale scores, loss of consciousness, length of posttraumatic amnesia, and neuroimaging techniques (CDC, 2015; Isella et al., 2003). Developments in the management and treatment of individuals with moderate to severe TBI have created an ever-growing number of survivors of brain injury; 87% of individuals are discharged from the hospital, most of whom experience some degree of physical, behavioral, cognitive, and emotional sequelae (CDC, 2015). Further, financial costs to society are estimated to be in the realm of 56.3 billion dollars annually (Thurman, 2001), both as a result of the cost of medical care and the resultant reduced productivity. These outcomes, however, may be particularly salient for ethnic minorities. Of the 2.2 million emergency department visits resulting from the injury each year in the U.S, more than half of the individuals are racial minorities (Center for Disease Control, 2010).

A Changing Demographic

The need to assess intellectual functioning accurately for racial minorities has become a paramount concern for clinicians. Perhaps most pressing is the number of minority adults who present for testing and therefore are at the mercy of such tests. The population of ethnic minorities in the U.S. is growing at an exponential rate (Colby & Ortman, 2015). According to the 2014 United States Census, Caucasians compose 78% of the population, Hispanics or Latinos, 17%, African Americans 13%, American Indians and Alaska Natives 1.2%, and Asians 5.4%. More striking though, are the projections for 2060. Although the number of Caucasians is expected to increase by 16%, the number of ethnic minorities is projected to increase at nearly double that rate (Colby & Ortman, 2015). To demonstrate, the number of African Americans is projected to increase by 42%, Hispanics by 114%, and Asians by 128% (Colby & Ortman, 2015). However, for brevity, this paper will largely focus on three of the four groups just listed (Whites, African Americans, and Hispanics), because these groups have composed the largest portion of the U.S. population (Colby & Ortman, 2015).

This rapid increase of ethnic minorities, coupled with the overwhelming impact of TBI on both the individual and on society underscores the necessity for improved post-injury assessments and outcomes. Moreover, numerous studies have found an association between racial minority status and poor post-injury outcomes, relative to White counterparts (Arango-Lasprilla, Ketchum, Willaims, Kreutzer, & de la Planta, 2008; Gary, Arango-Lasprilla, & Stevens, 2009).Thus, accurately quantifying the level of intelligence pre and post injury is imperative for detecting cognitive impairments, establishing rehabilitation options and providing financial compensation after a neurological injury (Green, Melo, Chistensen, Ngo, Monette, & Bradbury, 2008). Despite the high survival rate of individuals with TBI that are ethnic minorities (Cooper, Tabaddor, & Hauser, 1983; Bruns, & Houser, 2003), there is a paucity of research on the accuracy of premorbid estimates of intelligence after a brain injury, which compromises rehabilitative efforts.

Measurement of Intelligence

Measures of intelligence were originally developed to assist educators with differentiating levels of learning capacities in students, particularly in cases with students experiencing learning disabilities (Binet, Simon, & Town, 1915). Over time, both psychologists and educators have adopted tests of intelligence both in school environments as well as in clinical settings.

Cattell (1963) argued that there are two types of intelligence that make up the general intellectual factor (g); namely fluid and crystallized intelligence. Fluid intelligence is often defined as an individual's ability to reason abstractly, identify connections between relationships, and navigate through difficult problems. Accordingly, tests of fluid intelligence are typically nonverbal assessments that often require abstract reasoning and problem-solving skills (Okada de Olivera, Nitrini, Sanches Yassuda, & Brucki, 2014). Crystalized intelligence, on the other hand, is based on historical facts and acquired knowledge primarily derived through learning experiences and education (Okada de Olivera, et al., 2014; Willshire, Kinsella, & Prior, 1991). Tests that measure crystalized intelligence are composed of verbal measures, such as reading comprehension and vocabulary (Okada de Olivera, Nitrini, Sanches Yassuda, & Brucki, 2014; Willshire, Kinsella, & Prior, 1991). Although these two types of intelligence make up an individual's IQ, this paper will focus on how crystalized intelligence may be adversely impacted by social and economic factors, given its reliance on knowledge acquired through educational experiences.

For a valid interpretation of the meaning of each individual assessment score, intelligence testing instruments are systematically standardized and nationally normed. General population norms are derived from demographic characteristics, namely by an individual's age, gender, education level, occupation, and geographic region. Subsequently, individual performance scores are compared with scores derived from the general population average (Cicchetti, 1994). The use of a standard score can then be utilized to determine an individual's intellectual performance in comparison with same-aged peers (Cicchetti, 1994). However, although efforts have been made to make norms more representative of the general population, the normative samples remain disproportionate and appear to underrepresent some minority groups (Colby & Ortman, 2015). In a clinical setting, these factors may also be a source of the variance in neuropsychological test performance across some cognitive domains. For instance, a group of healthy African- Americans were inaccurately misclassified as "cognitively impaired" due to lower scores on measures of memory, processing speed, and visual spatial skills when using normed cut off ranges (Campbell, Ocampo, Combs, Ford-Booker, & Dennis, 2002). These results further suggest that some cognitive assessments may be lacking in the ability to conceptualize cognitive test performance accurately among individuals that are outside of the demographic composition of the normative population.

As noted by Brown, Reynolds and Whitaker (1999), racial differences in test scores may conceivably reflect, "no real differences in ability, but rather problems in the construction, design, administration, or interpretation of tests" (p. 209). To illustrate, a study evaluating the differential prediction of the widely used Wechsler Individual

Achievement Test (WIAT) scores from WISC-III FSIQ between African American, Hispanic, and Caucasian children noted a sample size for Caucasians that was, on average, five to seven times the size of African Americans' and Hispanics' sample sizes (Weiss & Prifitera, 1995). Similarly, the Wechsler Adult Intelligence Scale –Revised (WAIS-R), was normed using a standardization sample of 1,880 adults. When this sample was stratified by race, 1,664 were Caucasian, 162 were African-American and 24 were Non-White (Reynolds, Chastain, Kaufman, & McLean, 1987). Evidently, minority groups such as African Americans and Hispanics are underrepresented in the test construction samples of these intelligence tests; thus, inevitably favoring the largest represented group and leading to inaccurate assessments and misclassifications among minorities.

Group Differences in IQ

Research has shown significant group differences in IQ between African Americans and Caucasians; this discrepancy is often referred to as the Black/White gap (Valencia & Suzuki, 2001). In fact, the standardization sample of one of the most commonly used traditional IQ test for adults, the Wechsler Adult Intelligence Scale (WAIS-IV), showed significant group differences in IQ between African Americans (M = 88.7; SD = 13.68) and Caucasians (M = 103.2; SD = 13.77). Hispanics performed at the intermediate level (M = 91.6; SD= 14.29; Wechsler, 2008). Further, a number of studies have shown that Caucasians outperform African-Americans on verbal and nonverbal measures, such as the vocabulary and block design subtest of the Wechsler Adult Intelligence Scale –Revised (Kaufman, McLean & Reynolds, 1988; Marcopulos, McLain & Giuliano, 1997; Paolo, Ryan, Ward, & Hilmer, 1996). Given the group differences in

IQ test scores, many clinicians question if traditional IQ tests are more a reflection of the aforementioned inherent cultural bias of tests and other disadvantages associated with racial minority status rather than of intellectual ability (Weiss, Chen, Harris, Holdnack, & Saklofske, 2010). For this reason, some authors propose that in order to reduce possible sources of bias in a standardization sample, intelligence test developers must first identify the underlining variables that account for the largest variance between racial groups (Weiss, Saklofske, & Raiford, 2010). Perhaps more to the point, these group differences may not be a reflection purely of race, but rather of underlying circumstantial factors that may influence an individual's accessibility to resources. This research intends to focus on unequal educational experiences as a factor in driving the group differences in intellectual ability, regardless of race.

There is sufficient data supporting the idea that the Black/White gap is perhaps strongly influenced by the "structure of inequality"; that is, numerous sources associated with racial minority status and educational disadvantage (Wilson, 1998). Other researchers argue that intelligence is partially influenced by genetic factors (Bouchard & McGue, 1981). Although twin studies have compelling evidence to support this claim, many agree that such conclusions are uncertain due to the interrelationship between heredity and environment (Collins, Maccoby, Steinberg, Hetherington, & Bornstein, 2000). Over the years, research has focused on the influence of psychosocial factors and shifted toward exploring social inequalities in educational experiences as, perhaps, the main culprit in explaining these achievement gaps (Dotson, Kitner-Triolo, Evans, & Zonderman, 2009; Condron, 2009). Haveman and Smeeding (2006) noted that low SES had a significant influence on academic achievement and is especially evident in standardized test scores. In other words, children who are born into low-income families are at an educational disadvantage and predisposed to underperform on standardized exams. The impact of unequal education, however, may be particularly more salient for minorities, given the fact that they compose most of the low-income areas in the U.S (Jiang, Ekono, & Skinner, 2013). The National Center for Children in Poverty is currently reporting disproportionate numbers of African American and Hispanic children under age 9 years who are low income and poor. For instance, out of 15.4 million young children living in low income areas in the United States, 31% of all young White children are in low income areas; 64% of all African American young children, and 61% of all Hispanic young children in this group are low income (Koball & Jiang, 2018). Given the evidence that low-income areas are predominantly made up of racial minorities, the achievement gap may be a product of educational inequalities.

An Increase of Racially and Economically Concentrated Schools

Although legally imposed desegregation of schools came into effect in 1954, residential segregation along racial lines is strikingly higher now than in the last 4 decades (Glymore & Manly, 2008; Orfield, Kucsera, & Siegel-Hawley, 2012). School segregation appears to be a product of persistent residential segregation (Orfield et al., 2012). For decades, researchers have argued that school inequalities are largely driven by primarily two trends; (1) the amount of resources available across schools and (2) school segregation (Cook & Evans, 2000; Boozer, Krueger, & Wolken, 1992). Decades later, these trends still exist, as illustrated by the continued uneven distribution of racial groups among schools. For example, the 2012 Civil Rights Project is now reporting that African American and Latino students currently attend schools where the majority of children are in poverty (Orfield, Kucsera, & Siegel-Hawley, 2012). Further, African American and Latino students attend less racially diverse schools today than in the past 4 decades (Orfield, Kucsera, & Siegel-Hawley, 2012). According to a recent analysis from the U.S government and accountability office, over time there has been a large increase in the percentage of public schools in the United States with students that are poor and predominantly Black and Hispanic (2016). Thus, the impact of educational quality may be more salient for minority groups that are overrepresented in low-income areas.

Given the current unequal distribution of racial groups, one may also reasonably question if school racial composition is perhaps related to educational quality. In fact, some studies have found racial segregation in schools to be one of the main influencing factors in maintaining the black/white gaps in academic performance (Condron, 2009; Cook & Evans, 2000; Boozer, Krueger, & Wolken, 1992). Some authors argue that differences in reading scores between White and Black students is largely attributed to declines in quality of education for disadvantaged urban schools and schools with predominately Black students (Cook & Evans, 2000). This inequality in educational experiences is particularly important to point out, given the fact that crystalized intelligence is a fragment of the overall IQ score, and is largely developed through educational experiences.

Additionally, students who attend schools in poor areas may experience the ramifications of living in neighborhoods that have high crime rates, high rates of unemployment and low-quality services (Ainsworth 2002; Wilson 1998). These distal factors within an individual's environment may indeed also interfere with obtaining access to resources and educational attainment (Ainsworth 2002). Further, impoverished environments can adversely affect IQ. For instance, studies suggest that children living in low income areas, associated with higher crime rates, unemployment, and low-quality services (Wilson, 2012; Sampson & Morenoff, 1997), are also at risk of encountering undernourishment. Consequently, these children are more likely to be exposed to agents that may reduce brain development and intelligence, such as lead (Bellinger & Needleman, 2003). If social and economic deprivation negatively impact intelligence (Brooks-Gunn &Duncan, 1997), and minority students compose most of the low-income schools, these factors also likely adversely impact educational experiences and IQ test scores.

The Impact of Education Inequality on IQ Scores

The widespread social inequalities in educational experiences may play a role in the alarming racial disparities in IQ measures. In fact, a growing number of cross-cultural researchers have suggested that differences in quality of education maintain racial disparities in cognitive test performance (Smith & Welch, 1977; Glymore & Manly 2008). Bryant (2015) analyzed high-school education data and academic success for students who live in poverty and found that high poverty schools had higher numbers of less experienced and less qualified teachers, fewer counselors, and fewer college prep courses than schools located in low poverty areas. In fact, students from disadvantaged areas seem to be placed into lower/slower learning groups than their advantaged peers (Condron, 2007). In a group of first graders from the Early Childhood Longitudinal Study-Kindergarten Cohort, disparities in reading group placement by SES, race/ethnicity, gender, and family structure were found (Condron, 2007). Specifically, minority students were disproportionately represented in lower level tracks, which are often characterized by lower quality curricula and instruction. Moreover, attending schools that comprise minority students has been shown to inhibit both reading and math gains when compared with schools that comprise predominately White students (Condron, 2009). For instance, a study examining the effects of attending a minority segregated school versus a White segregated school in a sample of 3,442 1st graders revealed a significant impact on math and reading gains over the course of the school year, such that minority segregated schools underperformed relative to White segregated schools (Condron, 2009).

Most recently, the U.S government and accountability office reported that racially and economically concentrated schools offer fewer resources and disproportionately fewer math, science and college prep courses, compared with other schools (U.S GAO, 2016). Further, the U.S. Department of Education Office of Civil Rights (2014) reported that schools with the highest percentage of African American and Latino students in the U.S. have less access to “college preparedness courses,” such as algebra II and chemistry (Glymore & Manly, 2008). Although this review alludes to college and career readiness for minority students, school quality differences often extend to all components of schooling, such as textbooks and syllabi, teacher training, class size, and school hours (Glymore & Manly, 2008). For instance, students from low socioeconomic backgrounds who attend poorly funded schools have been shown to underperform in academic achievement (Eamon, 2005). Additionally, students with low SES have been found to have lower test scores and higher dropout rates than students with high SES (Eamon, 2005). For the same reason, even among Caucasians, low-quality education may impact intellectual abilities (Glymore et al., 2008; Glymore & Manly, 2008). Although not as heavily represented, Caucasians that live in low-income areas have also been found to underperform when compared with Caucasians from high SES backgrounds (Dotson, Triolo, Evans, & Zonderman, 2009). Similarly, studies have shown that Caucasians who attend school in states that are less academically demanding have worse memory scores than Caucasians from other states with strict school regimens (Glymore et al., 2008). Further, a study comparing cognitive abilities between high SES and low SES individuals found that years of education predicted cognitive performance for only high SES Caucasians, but was not associated with any cognitive abilities in African Americans and low SES Caucasians (Dotson, Triolo, Evans, & Zonderman, 2009). This speaks directly to the need for variables other than years of education when attempting to predict cognitive performance of minorities and anyone of low SES.

Poverty appears to impact educational experiences negatively regardless of racial background; however, in the United States, minorities such as Hispanics and African Americans have been shown to make up most of the poor income areas (Strauss, Sherman, & Spreen, 2006). These racially and economically concentrated schools that offer fewer resources are, perhaps driving the well-known relationship between racial classification and cognitive test performances. Therefore, measures that rely on the number of years of education without accounting for educational quality may be less accurate in measuring cognitive ability. Environmental factors appear to play a critical role in shaping an individual's overall educational experience and have been found also to impact an individual's IQ adversely (Bellinger & Needleman, 2003, Brooks-Gunn & Duncan, 1997). In fact, some authors have found that differences in IQ scores are largely reduced when controlling for social and economic factors (Nisbett, 2009). These findings have underlined the necessity to consider differences in social inequalities as an influencing factor when interpreting IQ scores that are not entirely normed to represent individuals across different developmental and social experiences. Considering differences in educational inequalities will now be examined in relation to the utility of IQ scores in clinical settings.

Estimating Premorbid IQ

Ideally, clinicians and researchers would quantify intellectual impairments by comparing a patient's previous performance on psychometric tests of IQ before (premorbid IQ) and after an etiologic event, such as a brain injury, neurodegenerative disorder, or other cerebral dysfunction (Crawford, Stewart, Cochrane, Foulds, & Besson, 1989). Unfortunately, premorbid IQ scores are rarely available (Crawford et al., 1989; Griffin, Rivera-Mindt, Rankin, Ritchie, & Scott, 2002). Consequently, several different approaches have been developed to estimate premorbid intellectual functioning.

Using Regression Equations to Estimate Premorbid IQ

Demographic variables, such as an individual's age and years of education, have been closely related to IQ tests and traditionally used to norm cognitive assessments and estimate a patient's premorbid level of intellectual cognitive ability (Franzen, Burgess, & Smith, 1997; Griffin, Rivera-Mindt, Rankin, Ritchie, & Scott, 2002). Additionally, one of the most beneficial aspects of using demographic information to predict premorbid intellectual functioning is that the patient's demographic information is unaltered by any brain pathology (Powell, Brossart and Reynolds, 2003). Correspondingly, researchers have developed a guide for clinicians to combine demographic information into specific

IQ prediction algorithms (Barona, Reynolds, & Chastain, 1984; Krull, Scott, & Sherer, 1995).

The Barona Regression Equation

Wilson, Rosenbaum, Brown, Rourke, Whitman, and Grisell developed one of the earliest methods of using a regression algorithm to estimate an individual's IQ level (1978). This regression formula was developed using the WAIS standardization sample in 1955 to predict the WAIS IQ scores based on the individual's age, sex, race, education, and occupation (Wilson, et al., 1978). Notably, a regression formula using demographically based information to predict IQ levels was one of the first attempts in reducing disparities between the educational levels of individuals in the standardized sample of the WAIS (Franzen, Burgess, & Smith – Seemiller, 1997). Over time, the development of the Wechsler Adult Intelligence Scale –Revised (WAIS-R) was developed in 1981 to reflect a more accurate demographic composition population in the U.S. (Wechsler, 1981). Subsequent to the updates made on the WAIS, Barona et al. then developed a regression equation from the WAIS-R standardization sample of 1,880 subjects based on age, sex, race, education, occupation and region (Barona, Reynolds, & Chastain, 1984). Out of this set of variables, education, race, and occupation were significant variables in the prediction of performance of the WAIS-R, and accounted for the greatest variance in explaining performance on the measure (Barona, Reynolds, & Chastain, 1984). However, one of the limitations with the regression algorithm is that it underestimated IQs that are above 125 and overestimated IQs that are below 75, due to regressions to the mean (Barona et al., 1984; Reynolds, 1997). Nevertheless, the Barona equation has been shown to be dependable for individuals with IQs between 90 and 109, yielding a strong correlation (r = .78) between formula based IQ and obtained WAIS-R IQs (Eppinger, Craig, Adams, & Parsons, 1987).

Other empirical evaluations of regression algorithms have narrowed down the predictability of these variables a step further by suggesting that using a single variable, years of education, may be just as explanatory as a formula in predicting IQ. Supporting this perspective, Karzmark, Heaton, Grant, & Mathews found a 66% accuracy in prediction when using years of education alone (1985). These results may be due to the well–known association between SES and education level. More recent studies have shown that education alone accounts for 29 % of the variance in Full Scale IQ scores on the Wechsler Adult Intelligence Scale- Fourth Edition between African-American and Caucasians (Weiss, Saklofske, & Raiford, 2010). In fact, many test developers use level of education as a sole proxy for SES because of its high correlation with direct indicators of SES, such as household income and occupation, and because a reliable report of an individual's overall income is often difficult to ascertain (Weiss, Saklofske, & Raiford, 2010). Using an individual's level of education has proven to have its benefits when predicting cognitive ability and SES status. However, given the recent literature suggesting that years of education may not be capturing differences in quality of education (Byrd, Jacobs Hilton, & Manly, 2005; Johnson, Flicker, & Lichtenberg, 2006; Manly, Jacobs, & Touradji, 2002), there is an opportunity to incorporate this variable as a predictor of IQ among minority groups.

The Oklahoma Premorbid Intelligence Method (OPIE)

Most recently developed, the Oklahoma Premorbid Intelligence Method (OPIE) is an alternate regression equation designed to predict premorbid intelligence that combines the demographic information used in the Barona with the individual’s current performance on a subtest of the WAIS, namely the WAIS Vocabulary and Picture Completion tests (Powell, Brossart, & Reynolds, 2003; Krull et al., 1995). Although this regression algorithm has been validated in some brain-injured patients, it is often critiqued for using scores of a WAIS composite in the regression equation to predict the same score of the WAIS composite for post-injury cognitive performance (Franzen, Burgess, & Smith-Seemiller, 1997; Powell, Brossart, & Reynolds, 2003). In other words, the correlation between the generated estimated score from this regression equation and the scores obtained from an individual’s actual test performance may be inflated, given the fact that the WAIS subscales are used in both computations (Shoenberg et al., 2002).

Through the use of demographic information and current performance on cognitive tests, both the Barona and the OPIE have proven to be effective in predicting an individual’s estimated premorbid IQ for some populations, largely Whites (Barona Reynolds, & Chastain, 1984; Langeluddecke & Lucas, 2004; Franzen, Burgess, & Smith-Seemiller, 1997; Long & Ross, 1992). Nevertheless, there is room for improvement. These regression algorithms of estimated intellectual ability function under the assumption that years of education have the same implications across all individuals (Long & Ross, 1992). This assumption may be particularly misguided for minority populations whose unequal educational quality, as previously mentioned, has impacted intellectual achievement and wage earnings (Baker, Johnson, Velli, & Wiley, 1996). The impact of psychosocial factors cannot be minimized when evaluating an individual’s performance. In order to further improve the accuracy of these regression equations, and perhaps help the formulas become more uniquely tailored to each individual, it is worth exploring variables that could better capture an individual's educational experience, ones that are not utilized as a subtest of the WAIS assessment of overall Intelligence.

Reading Level as a Promising Alternative in Predicting Cognitive Ability

Although education attainment has been shown to be a strong indicator of cognitive abilities for some populations and traditionally have been used to norm cognitive assessments, a growing body of research is suggesting that reading ability may be a better predictor of intellectual level of functioning for African-Americans (Byrd, Jacobs, Hilton, Stern, & Manly, 2005; Johnson, Flicker, & Lichtenburg, 2006; Manly et al., 2002). In fact, one study found significantly lower scores for African-American elders, compared with Whites in word list learning and memory measures, figure memory, and abstract reasoning, despite the group being matched by years of education (0-8, 9-11, 12-15 and greater than 16), which highlights the nuances of the years of education variable. However, disparities between racial groups greatly reduced after adjusting for quality of education, measured by reading level score (Manly et al., 2002). For this reason, some studies have suggested that reading level predicts cognitive ability better than the reported years of education; this is true, perhaps because it captures aspects of educational quality and is a more accurate representation of the ethnic differences that exist when predicting intellectual level of functioning (Byrd, Jacobs Hilton, & Manly, 2005; Johnson, Flicker, & Lichtenberg, 2006; Manly, Jacobs, & Touradji, 2002). In fact, some studies have found that reading level predicted performance on the California Verbal Learning Test, Benton Visual Retention test, Animal Fluency, Card Rotation Test, Brief Test of Attention, and Digit Span, better than years of education in a sample of African Americans who were predominantly of low

SES (Dotson, Kitner-Triolo, Evans, & Zonderman 2008). Indeed, the impact of literacy on cognitive performance has been well established in the literature (Ardila, Ostosky-Solis, Rosselli, & Gomez, 2000; Manly et al., 1999, 2000; Manly, Byrd, Touradji, Sanchez, & Stern, 2004). As a result, using reading level as a proxy for quality of education has proven to be a promising alternative for gauging an individual's level of cognitive ability.

Although research findings are encouraging in the healthy population, the impact of education quality, indexed by reading level scores, is surprisingly and rarely explored in clinical populations. One study by Ryan et al., found that African-Americans and Hispanics had inconsistent education attainment and quality (measured by reading level), compared with Whites in a group of individuals with HIV (2005). Thus, using measures that accurately capture an individual's quality of education is essential when attempting to classify an individual's overall level of cognitive decline and/or impairment in the clinical population.

Using reading level may be particularly useful in estimating an individual's previous cognitive ability after a brain injury, especially in light of the literature suggesting that reading level is relatively preserved despite any brain pathology (Franzen, Burgess, & Smith-Seemiller, 1997; Green, Christensen, Ngo, Monette, & Bradbury, 2008; Silverberg, Hanks, & Tompkins, 2013); this taps into premorbid knowledge yet minimizes the demands of current cognitive aptitude (Franzen, Burgess, & Smith-Seemiller, 1997; Green, Christensen, Ngo, Monette, & Bradbury, 2008; Silverberg, Hanks, & Tompkins, 2013). Furthermore, reading level has been shown to be more resistant to dementia than tests that are designed to measure an individual's fund of knowledge, such as WAIS Vocabulary subtest (Willshire, Kinsella, & Prior, 1991). Although some studies have found that performance on the National Adult Reading Test (NART) is affected by brain injury in some patients, other studies have shown a relatively preserved performance on the NART after brain injury (Crawford, Parker, & Benson, 1988). Another more recently developed word reading measure, namely the Wechsler Test of Adult Reading (WTAR) has proven to be an improved version of the NART (Holdnack, 2001). In fact, some clinicians have used the WTAR reading level score alone as an estimated premorbid measure of intelligence primarily because it was co-normed with the widely used WAIS intelligence test, thus improving the comparative analysis between predicted and actual cognitive performance over the NART (Holdnack, 2001). Because the WAIS is widely used to obtain a person's actual intellectual functioning, using a shared normative dataset with the WAIS to standardize the WTAR serves to minimize the error variance when clinicians opt to compare the WTAR reading level score (estimated IQ) to actual performance scores (Strauss, Sherman, & Spreen, 2006). Studies attempting to validate the WTAR in brain-injured individuals indicated high stability in WTAR scores during their recovery from Assessment 1 ($M = 34.25/50$) to Assessment 2 ($M = 34.21/50$; $r = .970$, $p < .001$), and significantly improving on three tests of current cognitive ability namely, measures of working memory, verbal abstract reasoning and visuospatial abilities, highlighting the stability of the WTAR (Green et al., 2008). Because some improvement in cognitive functioning is typically expected during an individual's recovery period after a brain injury (TBI Model Systems, 2010), the stable reading score across multiple time periods throughout recovery provides support for preserved word reading abilities.

Given the clinical utility of reading level assessments, in conjunction with research suggesting that reliance only on years of education may not account for quality of education (Dotson, Kitner-Triolo, Evans, & Zonderman 2008; Manly, Jacobs, & Touradji, 2002), methods that combine demographic information with current reading ability offer a reasonable method to estimating a patient's premorbid level of intelligence.

In support of the compelling logical conclusions regarding the utility of reading ability as a potential valuable variable in the prediction of premorbid intellectual functioning, Silverberg et al. recently explored the impact of educational quality, measured by reading ability, on cognitive test performance in patients with moderate to severe traumatic brain injury (2013). Similar to other findings, this study reported that reading levels predicted performance on the overall cognitive test battery mean better than years of education for minority patients (Silverberg, Hanks, & Tompkins, 2013). Specifically, they found that race and education added little to no value when compared with the WTAR word reading score in predicting the neuropsychological outcome (Silverberg, Hanks, & Tompkins, 2013). This research further supports the claim that perhaps reading ability is a better indicator of cognitive abilities because is captures educational quality, regardless of race and reported years of education. Still, there is a paucity of research examining the impact of educational quality, operationalized by reading level, on regression models of estimated premorbid intelligence. The dearth of literature in this area may result in misdiagnosing minorities from disadvantaged areas with cognitive impairment. Specifically, low scores of estimated intelligence derived from current regression equations may be the product of low quality of education rather than overall cognitive ability due to an ethnically biased operationalization of education.

With these considerations in mind, a revised WTAR measure that captures the aforementioned demographic characteristics was recently developed, namely the Test of Premorbid Functioning (Wechsler, D., 2009).

Test of Premorbid Functioning

The Test of Premorbid Functioning (TOPF) was published in 2009 as part of the Advanced Clinical Solutions (ACS) for the Wechsler Adult Intelligence Scale –Fourth Edition (Wechsler, D., 2009). This single word reading measure provides the option to consider demographic characteristics such as region, sex, race, years of education, occupation, perceived neighborhood wealth, elementary school quality, and parent's occupation when estimating IQ. Through the ACS computer software, clinicians have the option to choose between using (1) a TOPF reading level score alone, (2) a demographics predictive model only, or (3) demographics information combined with the TOPF reading level score as means to estimate an individual's premorbid IQ (Wechsler, D., 2009). Within the demographics predictive models, the clinician may select between the simple or complex demographics modules. The simple demographics includes the examinee's region, sex, race, years of education, and occupation, whereas the complex model adds other factors such as perceived neighborhood wealth, elementary school quality, and parent's occupation (Wechsler, D., 2009). The validation process for the TOPF included 2,152 participants, ages 16-90. Through the use of regression equations, demographic data were used to predict performance on the TOPF reading measure in a group of 20-year-old to 90-year-old participants. Results showed that education, occupation, region and race/ethnicity were the best predictors, with years of education accounting for the greatest variance in reading level (Wechsler, D., 2009). Similarly, when attempting to predict FSIQ using the same demographically based independent variables, years of education accounted for the greatest variance in performance (Wechsler, D., 2009). After adding variables, such as personal factors (hours of sleep the night prior, current neighborhood wealth, job change, activity level) and developmental factors (elementary school quality, neighborhood wealth as a child, parent's years for education and occupation), improved the overall prediction of FSIQ and lessened the effect of education. Interestingly, the combined simple demographics with the TOPF reading measure was found to be the improved predictor of FSIQ. Although using the complex demographics with the TOPF did not improve the prediction of FSIQ, compared with the simple demographics with TOPF model, the former model reduced the predictive value of the race variable. This finding suggests that adding personal and developmental factors may give a better estimation of different experiences that are beyond race, such as educational quality, allowing for a more individually tailored approach in estimated intelligence.

Evidently, the ideal measure of estimated intelligence is one that is individualized and built to capture an individual's demographic and developmental factors accurately. However, although this newly developed measure is promising, little is known about the efficacy of the TOPF across different populations (Wechsler, D., 2009).

Literature Review Summary and Hypotheses

Clinicians and researchers face challenges when attempting to assess cognitive decline. Incidences of brain injury are on the rise and, as the demographics in the United States shift, incidences among minorities will continue to grow as well. Given the abrupt and often unforeseen nature of many TBIs, access to premorbid IQ is rare and clinicians are left without a crucial data point. As a result, continued research aiming to enhance measures of estimated premorbid intelligence is imperative. The reviewed research builds a strong case to suggest that years of education, as a variable, may be insufficient when it comes to estimating premorbid IQ, particularly among minorities. Replacing that variable with one that captures educational quality may yield a more accurate premorbid IQ score. The reviewed research also supports the use of reading level tests as a good proxy for quality of education. This approach leverages previous clinical applications of reading level measures by exploring its influence on a well-known regression equation of estimated intelligence. This study aims to further support the utility of certain demographic characteristics, such as quality of education, as a potential method to improve the prediction accuracy of premorbid intellectual functioning. The next section elaborates further on the proposed investigation, and provides a detailed account of the methods that will be used.

Research Questions and Hypotheses

(1) Will an adjusted regression equation, including a new education variable (reading level), yield stronger predictive ability of IQ among African Americans and Hispanics when compared with the Barona regression equation (age, sex, years of education, occupation and region)?

(2) Is there a relationship between school factors, such as racial composition, school location's poverty level (SLPL) and reading level scores?

Hypothesis 1

H_1: It is predicted that an adjusted regression equation, including a new quality of education variable, WTAR reading level, will yield stronger predictive ability of FSIQ among African Americans and Hispanics when compared with the variables used in the Barona regression equation (which includes the following variables: age, gender, race, education, occupation and geographic regions of the U.S.). It is also predicted that the adjusted regression equation will yield stronger predictive ability of FSIQ among TBI patients, compared with the Barona regression equation.

Hypothesis 2

H_2: Given prior research showing a relationship between level of segregation in schools and quality of education (Condron, 2009; Cook & Evans, 2000; Boozer, Krueger, & Wolken, 1992), it is predicted that school racial composition, school location's poverty level (SLPL) and reading level scores will be significantly correlated. Specifically, it is hypothesized that there will be a significant relationship between racially segregated schools (i.e., % of minority students in the subject's elementary school), SLPL (% of poverty level of the area where the school was located) and quality of education (reading level raw score).

Chapter 3: Methodology

The current study draws from an archival dataset that was specifically designed to assess apathy, executive functioning skills and cognitive fatigue in a group of individuals with Traumatic Brain Injury. This study focused on the impact of quality of education, measured by reading level, on a regression-based method of premorbid intelligence.

Design.

The present study will address the aforementioned hypotheses by investigating a quantitative, retrospective, correlational design for predicting premorbid IQ in brain injured and healthy adults. With the intent of determining if reading level is a stronger predictor of premorbid IQ than years of education for African Americans and Hispanics, the current study employed correlational and multiple regression analyses.

Participants.

Participants in the archival dataset consist of a total of 110 individuals with moderate to severe TBI and non-brain injured healthy controls. Eligibility criteria included age, ranging from 18 - 65 years and a documented TBI, as defined by the Traumatic Brain Injury Models System: "damage to brain tissue caused by an external mechanical force, as evidenced by loss of consciousness due to brain trauma, post-traumatic amnesia, skull fracture, or objective neurological findings that can reasonably be attributed to TBI on physical examination or mental status examination" (Model Systems Knowledge Translation Center [MSKTC]). Inclusion also required a moderate to severe TBI, as measured by a score below 13 on the Glasgow Coma Scale (GCS) in the first 24 hours following injury (CDC) and at least 1 year post injury. In the event that

GCS scores were not available, subjects were included if medical documentation was sufficient to allow for post estimation of GCS. Participants were initially recruited through clinics at UMDNJ, the Northern New Jersey TBI Model System, and the Kessler Rehabilitation System. Subjects were also selected from the Kessler Lab database, in accordance with institutional and HIPAA rules. Persons with a significant history of substance abuse, as documented by the Michigan Alcohol Screening Tests (Seltzer, 1971) or significant psychiatric history (e.g., Schizophrenia, Bipolar Disorder, Major Depression) were excluded. Additional exclusion criteria were any neurological illness other than TBI (e.g., epilepsy, MS), learning disability or lack of fluency in the English language. The participants were ethnically diverse and identified themselves most commonly as White, Latino, African American, or Asian.

Measures.

Demographics. A general demographics form was administered via phone to gather a participant's gender, age, race, years of education. An additional questionnaire gathered information regarding occupation, geographic region, participant school location and school racial composition. Data gathered in the study remained anonymous so that the names of the participants will not be linked to the subject ID.

The Barona Regression Formula. The Barona regression-based formula for estimating IQ was developed using the standardization sample of 1,880 subjects from the WAIS-R for estimating premorbid IQ (Barona et al., 1984). The regression equation variables for estimated Full Scale IQ are as follows: Estimated FSIQ = 54.96 + 0.47 (age) + 1.76 (gender) + 4.71 (race) + 5.02 (education) + 1.89 (occupation) + 0.59 (region). The Barona has been shown to be fairly reliable for individuals with IQs between 90 and 109, yielding a strong correlation (r = .78) between formula based IQ and obtained WAIS-R IQs (Eppinger, Craig, Adams, & Parsons, 1987). Research also has shown, however, that the formula tends to underestimate individual's IQs that are above 125 and overestimate individual's IQs that are below 75 (Barona et al., 1984; Reynolds, 1997). For this study, that computation of this formula was not used; rather, the variables in the Barona were used as predictors of WASI FSIQ. Additionally, selected variables were coded differently from the Barona. For instance, race was coded into only two categories (Caucasian and minorities; minorities comprised African American and Hispanics participants), age and years of education were used as continuous variables, and occupation was coded into three categories (skilled, semi-skilled, and not in the labor force).

The Wechsler Test of Adult Reading (WTAR). In light of recent research indicating that reading level captures an individual's quality of education (Byrd, Jacobs, Hilton, Stern, & Manly, 2005; Johnson, Flicker, & Lichtenburg, 2006; Manly et al., 2002), this current study used the WTAR as a proxy for quality of education. The WTAR is composed of a list of 50 words that have atypical grapheme-to-phoneme translations for oral word reading (Psychological Corporation, 2001; Lezak, 2004). Reading recognition is relatively stable in the presence of brain injury, and the WTAR therefore allows an initial estimation of pre-morbid intellectual and memory abilities (Willshire, Kinsella, & Prior, 1991). The test takes less than 10 minutes to administer and is normed with the Wechsler Adult Intelligence Scale-Third Edition (WAIS–III; Wechsler, 1997a) and Wechsler Memory Scale-Third Edition (WMS–III; Wechsler, 1997b); these have been shown to correlate highly with measures of verbal IQ (r = .75), verbal comprehension (r = .74), and full-scale IQ (r = .73; Strauss, Sherman, & Spreen, 2006).

Higher scores represent higher estimates of reading level.

The Wechsler Abbreviated Scale of Intelligence (WASI). The WASI was developed as a short and reliable measure of intelligence in clinical population. The WASI has shown excellent internal consistency reliability on all three of its major scales (VIQ = .96; PIQ = .96; FSIQ = .98; Psychological Corporation, 1999). In addition, construct validity has been consistently supported by high intercorrelations between the WASI subtests with WAIS-III IQ scales (range: .66 - .92), as well as by factor analysis (Psychological Corporation, 1999).

WASI Vocabulary Subtest. The WASI Vocabulary subtest assesses vocabulary and verbal knowledge (Psychological Corporation, 1999). This task consists of the individual presentation of 42 English words in order of difficulty that the subject is asked to define orally. A score of 0, 1, or 2 is obtained for each word, based on the completeness and accuracy of the definition provided. Utilizing vocabulary as a measure of general intelligence is a common procedure in neuropsychological research.

WASI Block Design Subtest. The Block Design subtest consists of a set of 13 modeled or printed two-dimensional geometric patterns that the examinee replicates within a specified time limit using nine red and white cubes. This subtest assesses an individual's spatial visualization abilities, visual-motor coordination, and abstract conceptualization.

WASI Similarities Subtest. The Similarities subtest contains four picture items and 22 verbal items. For items 1-4, the examinee sees pictures of three common objects on the top row and four response options on the bottom row. The examinee responds by pointing to the one response item that is similar to the target items. For each verbal item, a pair of words is presented orally and the examinee is asked to explain the similarity between the items presented. The Similarities subtest is a measure of verbal concept formation, abstract verbal reasoning abilities, and general intellectual ability.

WASI Matrix Reasoning subtest. The WASI Matrix Reasoning subtest assesses nonverbal reasoning (Psychological Corporation, 1999). This task consists of 35 incomplete patterns, which the subject completes by choosing the correct pattern from five possible choices; a score of 0 or 1 is given. Matrix reasoning is a measure of nonverbal fluid reasoning and general intellectual ability.

The Sociodemographic Questionnaire (SDQ). The SDQ was used to evaluate the sociodemographic variables. The SDQ was chosen for this study because it is one of the few measures intended for evaluating the sociodemographic variables in adults, and is relatively easy to administer and score. Specifically, this measure consists of 56 questions, which allow for parsing out aspects of SES, such as living situation, financial history and educational background. This study focused on the questions associated with educational background, such as “Where did you attend elementary school (city and state)?” Was your elementary school in a rural, suburb, urban or military area?” “What percentage of students in your elementary school were Black/AA, Hispanic/Spanish-Speaking, White and Other?” “What percentage of teachers in your elementary school were AA, Hispanic, White, and Other?” Data regarding the location of the elementary school (City, State) was used to ascertain the poverty level of each subject’s elementary school locations, using the U.S Census population calculator (Data Access and Dissemination Systems; DADS).

Procedures.

A retrospective study will be conducted using archival data from the Kessler Foundation Neuroscience and Neuropsychology Laboratory. All participants in the dataset were screened via telephone for age, time since TBI, neurological, psychiatric and substance abuse history, and currently taken medications. Prior to participation in the study, all participants were required to sign an informed consent form approved by the Institutional Review Board. Participants also completed a broad-based neuropsychological assessment battery to evaluate the participant's cognitive abilities fully. The cognitive measures included were standard measures of overall intellectual functioning, attention/concentration, working memory, information processing speed, verbal learning and memory, executive functions, depression, and anxiety. Participants were also asked to complete a questionnaire identifying the location of their elementary schools in addition to each school's racial composition in percentages.

To ensure treatment fidelity throughout the data collection period, all neuropsychological measures were read verbatim from a script and administered by the same person. The hard copies of the test administration forms were reviewed and entered by a researcher into a new de-identified dataset. Before acquiring the dataset, approval from the PCOM IRB was obtained. All data was maintained and analyzed using SPSS.

Statistical Plans and Analysis

Statistical Plan for Hypotheses 1: It is hypothesized that the inclusion of a reading level score variable will yield stronger predictive ability of IQ among minorities (African Americans and Hispanics) when compared with the Barona regression equation (age, gender, education, race, occupation and geographic region). To test this hypothesis, hierarchical multiple regression analyses were completed. The predictor variables were demographic data used in the original Barona regression equation, with FSIQ as the outcome variable. The demographic variables used in the Barona were entered first to determine how well they predict FSIQ. Then, the reading level score was added to the model to determine the unique contribution to the prediction of FSIQ above and beyond the variables used in the Barona equation. This hierarchical regression model was also tested among TBI patients, specifically, in order to determine whether or not the adjusted equation yielded stronger predictive ability than the Barona equation for this population. Standardized test scores, such as the FSIQ were entered as standard scores.

Statistical Plan for Hypotheses 2: It is also hypothesized that there is a significant relationship between percentages of school racial composition, SLPL, and quality of education (reading level score). To test this hypothesis, a Pearson correlation analysis was conducted.

Chapter 4: Results

Selection of Participants

To investigate the influential properties of the reading level score on the Barona equation in a clinical and nonclinical sample, all archival data were reviewed. Of the 110 participants, only 66 completed all required fields (i.e., age, gender, years of education, race, occupation by skill level, geographic region, WTAR reading score and the WASI FSIQ) for the testing of the first hypothesis after a listwise deletion method was employed. After the data were stratified into groups, 43 participants were in the TBI group and 23 were non-TBI group. Last, for the second hypothesis, only 35 participants completed the educational experience portion of the demographic questionnaire. In order to make accurate conclusions regarding correlations between the school racial composition percentages, SPL, and quality of education, a listwise deletion method was employed, which subsequently left 35 participants for testing the second hypothesis.

Power Analyses

To calculate a sufficient sample size for the appropriate tests to be carried out, power analyses were conducted through a G*Power a priori sample size calculator for the three hierarchical multiple regressions using the fixed model, R^2 increase. For each of the hierarchical multiple regressions, the desired effect size was .15 (moderate), the power level was .95, the total number of predictors was six, and the probability level was .05. Based on this information, the minimum required sample size was calculated to be at 89 participants. Given the fact that there were a total of 66 participants to test for hypothesis 1, the actual power achieved was .87.

For the one-tailed correlations, the desired effect size was .50 (medium), the power level was .95, and the probability level was .05. Based on this information, the minimum required sample size was calculated to be at 46 participants. Given that there were a total of 35 participants to test for hypothesis 2, the actual power achieved was .87.

All analyses were computed using the statistical software program, SPSS. Descriptive statistics were used to gather demographic information about the sample, including reported age, gender, race, years of education, occupation by skill level, and geographic region. Participants also completed the following assessment measures: WASI, FSIQ, and WTAR.

Demographic and assessment data, reported as frequencies, means, standard deviations, and percentiles, are outlined in Table 1 and 2. Of the 66 individuals who participated in the study, 34.8% were in the non-TBI control sample, and 65.2% were in the brain-injured clinical sample (see Table 1). In terms of gender, 40.9% were female and 59.1% were male. The mean age of participants was 38.8. Of participants who completed the study, 72.7% identified as White/Caucasian; 27.3% were Black/African American or Hispanic/Latino/a (Minorities). Regarding the occupation in which the participants practiced, 48.5. % were in a skilled labor; 39.4% were in semi-skilled labor, and 12.1% were not in the labor force. In terms of years of education, the mean was 14.3. The mean WASI FSIQ score of the participants who took part in the study was 106.1 and the mean word reading (WTAR) was 37.1. Of the 66 participants, 35 completed a questionnaire addressing school related factors, namely the participant's elementary school poverty level and percentage of minorities in the elementary school (see Table 2).

Table 1. *Demographic and Assessment Characteristics of All Participants*

Characteristic	N (%)	Mean (SD)
Clinical vs. Control Sample		
TBI	43 (65.2)	
Non-TBI	23 (34.8)	
Gender		
Female	27 (40.9)	
Male	39 (59.1)	
Race		
Caucasian	48 (72.7)	
Minorities	18 (27.3)	
Occupation by Skill Level		
Skilled Labor	32 (48.5)	
Semi-Skilled Labor	26 (39.4)	
Not in the Labor Force	8 (12.1)	
Geographic Region		
North Eastern Region	66 (100)	
Age		38.8 (12.1)
Years of education		14.3 (1.8)
WTAR Total Correct		37.1 (8.4)
WASI FSIQ		106.1(13.3)

Note. Minorities = African American and Hispanics; WTAR= Wechsler Test of Adult Reading; WASI FSIQ = Wechsler Abbreviated Scale of Intelligence Full Scale Intelligence Quotient.

Table 2. *Descriptive Statistics for School Related Factors*

Characteristic	N (%)	Mean (SD)
SLPL %	35 (100)	13.8 (10.5)
Minority students in primary school %	35 (100)	38.0 (36.7)

Note: SLPL = School Location's Poverty Level

Hypothesis 1

Prediction of WASI FSIQ among All Participants

To discover whether or not reading level provided additional predictive value to the original Barona equation base model when predicting FSIQ among Whites, Blacks, and Hispanics, a hierarchical multiple regression analysis was performed.

The assumption of linearity was met, as assessed by partial regression plots and a plot of studentized residuals against the predicted values. The assumption of independence of residuals was also met, as evidenced by a Durbin-Watson statistic of 1.91, which suggests the residuals are uncorrelated (Field, 2009). A visual inspection of a plot of studentized residuals versus unstandardized predicted values revealed that the assumption of homoscedasticity was met. An examination of correlation matrices to assess for multicollinearity was found not to be an issue because none of the correlation coefficients were above .90, indicating no strong relationships. Correlation coefficients, displayed in Table 3, ranged in value from -.78 to .59, and the variance inflation factor (VIF) values were acceptable because they ranged between 1.10 and 3.16 (Field, 2009). The assumption of normality was also met, as assessed by P-P plot.

Table 3.

H^1 Assessment of Multicollinearity Among Full Scale IQ Predictors

	Correlation Coefficients						
	WASI_ FSIQ	Age	Gender	Race	Education (yrs)	Skilled	Semi-Skilled
Age	-.08						
Gender	.34**	-.02					
Race	-.22*	.10	.04				
Education (yrs)	.34**	.16	.27*	-.21*			
Skilled	.14	.10	.12	-.05	.26*		
Semi-Skilled	-.24*	.13	-.17	.13	-.23*	-.78**	
WTAR	.59**	-.01	.40**	-.10	.39**	-.03	-.14

*$p < .05$. **$p < .01$
Note: WTAR = Wechsler Test of Adult Reading

In the first step of hierarchical multiple regression, six predictors were entered: age, gender, education, race, skilled labor, and semi-skilled labor. Geographic region was deleted from the analysis, given that all participants were from the northeastern region. The Full-Scale IQ (FSIQ) was the outcome variable in the model to determine how much variance was accounted for the by six predictors. This model was statistically significant *F* (6, 58) = 3.07; p <. 001 and explained 24% of variance in FSIQ (see Table 4). Gender would have made a significant, unique contribution to the model; however, given the fact that three regression analyses have been performed on the data (TBI plus Healthy Controls, only TBI, and only Healthy Controls) as well as a correlation analysis (Hypothesis 2), a Bonferroni correction yielded a critical p-value set to .0125. After entry of word reading (WTAR) at Step 2, the total variance explained by the model was 42%

(*F* (7, 58) = 5.97; p <. 001). The introduction of word reading (WTAR) explained an additional 18% of variance in FSIQ (R^2 change =.18; *F* (1, 58) = 18.05; p <. 001). In the final adjusted model, word reading (WTAR) was a statistically significant predictor of FSIQ, *p* <. 001.

Table 4.

Models 1 and 2 Summary for All Participants

Model	R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	*df*1	*df*2	Sig. F change
1	.488[a]	0.238	0.160	12.19543	0.238	3.067	6	59	0.011
2	.647[b]	0.419	0.349	10.74144	0.181	18.054	1	58	0.000

a. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled to the dependent variable (WASI FSIQ)
b. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled, WTAR Total Correct to the dependent variable (WASI FSIQ)

Table 5 demonstrates that Model 1 and Model 2 were both significantly better at predicting FSIQ than the mean. Model 1 yielded an F ratio of 3.07, *p* < .012 and Model 2 yielded an F ratio of 5.97, *p* < .001. Both models significantly improved the ability to predict FSIQ, but there was significant improvement in predictive ability of FSIQ, demonstrated by the second model (with the inclusion of the WTAR variable).

Table 5.

Overall Regression Analysis for All Participants

	Model	Sum of squares	*df*	Mean square	*F*	Sig.
1	Regression	2736.780	6	456.130	3.067	0.011[a]
	Residual	8774.978	59	148.728		
	Total	11511.758	65			
2	Regression	4819.802	7	688.543	5.968	.000[b]
	Residual	6691.955	58	115.379		
	Total	11511.758	65			

a. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled to the dependent variable (WASI FSIQ)

b. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled, WTAR Total Correct to the dependent variable (WASI FSIQ)

Table 6 shows both the standardized and unstandardized beta weights, as well as *t* test for each variable. Given that the Bonferroni corrected *p* value was set to .0125, the WTAR emerged as the sole significant predictor of FSIQ, $t(58) = 4.25$, $p < .001$. In summary, Hypothesis 1 was partially supported because the WTAR improved predictive ability of FSIQ; however, race was not a significant predictor of FSIQ. Therefore, the hypothesis that the WTAR would yield stronger predictive ability among minorities was not supported.

Table 6.

Coefficients of Predictor Variables to the Dependent Variable from Model 1 and Model 2

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	SE	Beta	*t*	Sig.
1 (Constant)	79.858	13.333		5.989	0.000
Age	-0.068	0.135	-0.062	-0.506	0.615
Gender	7.163	3.224	0.267	2.221	0.030
Race	-4.702	3.525	-0.159	-1.334	0.187
Education (yrs)	1.621	0.925	0.222	1.753	0.085
Skilled	-2.439	5.117	-0.092	-0.477	0.635
Semi-Skilled	-5.072	5.308	-0.188	-0.955	0.343
2 (Constant)	69.017	12.018		5.743	0.000
Age	-0.083	0.119	-0.075	-0.694	0.490
Gender	2.872	3.014	0.107	0.953	0.345
Race	-4.367	3.106	-0.147	-1.406	0.165
Education (yrs)	0.414	0.862	0.057	0.481	0.633
Skilled	3.267	4.703	0.124	0.695	0.490
Semi-Skilled	-0.329	4.807	-0.012	-0.069	0.946
WTAR Total	0.809	0.190	0.513	4.249	0.000

Note. Dependent variable is WASI FSIQ; SE = standard error.

Prediction of WASI FSIQ in the Non-Brain Injured Control Sample

To discover whether or not a word reading score provided additional predictive value to the original Barona equation base model when predicting FSIQ for just the non-brain injured control sample, a second hierarchical multiple regression analysis was performed.

The assumption of linearity was met, as assessed by partial regression plots and a plot of studentized residuals against the predicted values. The assumption of independence of residuals was also met, as evidenced by a Durbin-Watson statistic of 1.91, which suggests the residuals are uncorrelated (Field, 2009). A visual inspection of a plot of studentized residuals versus unstandardized predicted values revealed that the assumption of homoscedasticity was met. An examination of correlation matrices to assess for multicollinearity was found not to be an issue because none of the correlation coefficients was above .90, indicating no strong relationships. Correlation coefficients, displayed in Table 7, ranged in value from -.68 to .49, and the variance inflation factor (VIF) values were acceptable because they ranged between 1.06 and 3.42 (Field, 2009). The assumption of normality was also met, as assessed by P-P plot.

Table 7.

H[1] Assessment of Multicollinearity Among the Non-Brain Injured Control Sample

	Correlation Coefficients						
	WASI_ FSIQ	Age	Gender	Race	Education (yrs)	Skilled	Semi-Skilled
Age	-.19						
Gender	.15	.02					
Race	-.44*	.42*	.16				
Education (yrs)	.15	.08	.02	-.26			
Skilled	-.06	.08	.12	-.02	.18		
Semi-Skilled	-.24	.39*	-.08	.34	-.03	-.68**	
WTAR	.49**	-.30	.09	-.15	.18	-.35	.05

**p* < .05. ***p* < .01

Note: WTAR = Wechsler Test of Adult Reading

In the first step of the second hierarchical multiple regression, six predictors were entered: age, gender, education, race, skilled labor, and semi-skilled labor. Geographic region was deleted from the analysis, given that all participants were from the northeastern region. The Full-Scale IQ (FSIQ) was the outcome variable in the model to determine how much variance was accounted for the by six predictors. This model was not statistically significant F (6, 16) = 1.23; *p* >. 05 (see Table 9). In the second step of the hierarchical regression, which included the word reading variable (WTAR), the model did not reach significance (F (7, 15) = 1.83; *p* <. 001). Table 8 depicts the R^2 change, which demonstrated that the inclusion of the WTAR captured significantly more of the explained variance in the outcome variable, FSIQ, but nonetheless failed to achieve significance as an overall model (see Table 9).

Table 8.

Models 1 and 2 Summary for Non-Brain Injured Control Sample

Model	R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	*df*1	*df*2	Sig. F change
1	.561a	0.315	0.058	11.22832	0.315	1.225	6	16	0.344
2	.679b	0.461	0.209	10.28795	0.146	4.059	1	15	0.062

a. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled to the dependent variable (WASI FSIQ)

b. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled, WTAR Total Correct to the dependent variable (WASI FSIQ)

Table 9 demonstrates that Model 1 and Model 2 were not significantly better at predicting FSIQ than the mean. Model 1 yielded an F ratio of 1.23, *p* > .05, and Model 2 yielded an F ratio of 1.83, *p* > .05. Neither model was significant in its ability to predict FSIQ.

Table 9.

Overall Regression Analysis for Non-Brain Injured Control Sample

	Model	Sum of squares	*df*	Mean square	*F*	Sig.
1	Regression	926.622	6	154.437	1.225	.344[a]
	Residual	2017.204	16	126.075		
	Total	2943.826	22			
2	Regression	1356.197	7	193.742	1.830	.154[b]
	Residual	1587.629	15	105.842		
	Total	2943.826	22			

a. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled to the dependent variable (WASI FSIQ)

b. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled, WTAR Total Correct to the dependent variable (WASI FSIQ)

Table 10 shows both the standardized and unstandardized beta weights as well as *t* test for each variable.

Table 10.

Coefficients of Predictor Variables to the Dependent Variable from Model 1 and Model 2 (Non-Brain Injured Control Sample)

Model	Unstandardized Coefficients B	Unstandardized Coefficients SE	Standardized Coefficients Beta	*t*	Sig.
1 (Constant)	101.522	23.975		4.235	0.001
Age	0.154	0.253	0.163	0.607	0.553
Gender	4.957	4.855	0.217	1.021	0.323
Race	-8.655	6.002	-0.373	-1.442	0.169
Education (yrs)	0.696	1.595	0.100	0.436	0.669
Skilled	-9.860	7.873	-0.432	-1.252	0.228
Semi-Skilled	-11.653	9.692	-0.452	-1.202	0.247
2 (Constant)	69.422	27.137		2.558	0.022
Age	0.241	0.236	0.256	1.021	0.323
Gender	3.731	4.490	0.163	0.831	0.419
Race	-9.560	5.518	-0.412	-1.733	0.104
Education (yrs)	-0.316	1.545	-0.045	-0.205	0.841
Skilled	-3.630	7.849	-0.159	-0.463	0.650
Semi-Skilled	-8.235	9.040	-0.320	-0.911	0.377
WTAR Total	1.027	0.510	0.459	2.015	0.062

Note. Dependent variable is WASI FSIQ; SE = standard error.

Prediction of WASI FSIQ in the Brain Injured Clinical Sample

To discover whether or not a word reading score provided additional predictive value to the original Barona equation base model when predicting FSIQ for only the brain injured sample, a third hierarchical multiple regression analysis was again performed.

The assumption of linearity was met, as assessed by partial regression plots and a plot of studentized residuals against the predicted values. The assumption of independence of residuals was also met, as evidenced by a Durbin-Watson statistic of 1.91, which suggests the residuals are uncorrelated (Field, 2009). A visual inspection of a plot of studentized residuals versus unstandardized predicted values revealed that the assumption of homoscedasticity was met. An examination of correlation matrices to assess for multicollinearity was found not to be an issue because none of the correlation coefficients were above .90, indicating no strong relationships. Correlation coefficients, displayed in Table 11, ranged in value from -.83 to .57, and the variance inflation factor (VIF) values were acceptable because they ranged between 1.07 and 3.52 (Field, 2009). The assumption of normality was also met, as assessed by P-P plot.

Table 11.

H^1 Assessment of Multicollinearity Among the Brain Injured Sample

	Correlation Coefficients						
	WASI_ FSIQ	Age	Gender	Race	Education (yrs)	Skilled	Semi-Skilled
Age	.07						
Gender	.35*	.03					
Race	-.27*	-.05	-.11				
Education (yrs)	.37**	.24	.49**	-.25			
Skilled	.19	.14	.08	-.11	.27*		
Semi-Skilled	-.16	-.04	-.15	.09	-.28*	-.83**	
WTAR	.57**	.14	.49**	-.19	.41**	.01	-.12

*$p < .05$. **$p < .01$

Note: WTAR = Wechsler Test of Adult Reading

In the first step of the third hierarchical multiple regression, six predictors were entered: age, gender, education, race, skilled labor, and semi-skilled labor. Geographic region was deleted from the analysis, given that all participants were from the northeastern region. The Full-Scale IQ (FSIQ) was the outcome variable in the model to determine how much variance was accounted for the by six predictors This model was not statistically significant F (6 , 36) = 1.82; p >. 05. After entry of word reading (WTAR) at Step 2, the total variance explained by the model as a whole was 41%, a significant change in R^2 (see Table 12), and the model was significant in the prediction of FSIQ, F (7, 35) = 3.40; *p* <. 001. The introduction of word reading (WTAR) explained an additional 17% of variance in FSIQ (R^2 change =.17; F (1, 35) = 10.10; p <. 001). In the final adjusted model only one of seven predictor variables was statistically significant, with word reading (WTAR) recording a higher Beta value (β =. 69, p <. 001).

Table 12.

Models 1 and 2 Summary for All Brain Injured Clinical Sample

Model	R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	*df*1	*df*2	Sig. F change
1	.483[a]	0.233	0.105	12.05951	0.233	1.822	6	36	0.122
2	.636[b]	0.405	0.286	10.77444	0.172	10.099	1	35	0.003

a. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled to the dependent variable (WASI FSIQ)

b. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled, WTAR Total Correct to the dependent variable (WASI FSIQ)

Table 13 demonstrates that only Model 2 was significantly better at predicting FSIQ than the mean. Model 1 yielded an F ratio of 1.82, *p* > .05, and Model 2 yielded an F ratio of 3.39, *p* < .001. There was significant improvement in predictive ability of FSIQ demonstrated by the second model (with the inclusion of the WTAR variable).

Table 13.

Overall Regression Analysis for Brain Injured Clinical Sample

	Model	Sum of squares	*df*	Mean square	*F*	Sig.
1	Regression	1589.530	6	264.922	1.822	.122[a]
	Residual	5235.540	36	145.432		
	Total	6825.070	42			
2	Regression	2761.967	7	394.567	3.399	.007[b]
	Residual	4063.103	35	116.089		
	Total	6825.070	42			

a. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled to the dependent variable (WASI FSIQ)

b. Predictors: Age, Gender, Race, Years of Education, Skilled, Semi-Skilled, WTAR Total Correct to the dependent variable (WASI FSIQ)

Table 14.

Coefficients of Predictor Variables to the Dependent Variable from Model 1 and Model 2 (Brain Injured Clinical Sample)

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	SE	Beta	*t*	Sig.
1 (Constant)	70.686	16.653		4.245	0.000
Age	-0.023	0.163	-0.021	-0.139	0.890
Gender	6.850	4.235	0.255	1.617	0.115
Race	-5.386	4.674	-0.174	-1.152	0.257
Education (yrs)	1.485	1.146	0.220	1.295	0.203
Skilled	4.940	6.796	0.195	0.727	0.472
Semi-Skilled	3.078	6.776	0.122	0.454	0.652
2 (Constant)	63.542	15.047		4.223	0.000
Age	-0.075	0.147	-0.071	-0.513	0.611
Gender	2.131	4.065	0.079	0.524	0.603
Race	-3.949	4.200	-0.128	-0.940	0.354
Education (yrs)	0.600	1.061	0.089	0.566	0.575
Skilled	9.022	6.206	0.356	1.454	0.155
Semi-Skilled	6.220	6.134	0.246	1.014	0.318
WTAR Total	0.694	0.218	0.505	3.178	0.003

Note. Dependent variable is WASI FSIQ; SE = standard error.

Table 14 shows both the standardized and unstandardized beta weights, as well as *t* test for each variable. Given the Bonferroni corrected *p* value set to .0125, the WTAR emerged as the sole significant predictor of FSIQ, t(34 = 3.18, $p < .001$.

Hypothesis 2

To test the hypothesis that there is a relationship between school racial composition, school location' s poverty level, and quality of education, a Pearson correlation was conducted. Of the 66 participants in the study, only 35 participants completed the educational experience portion of the demographic questionnaire. Accordingly, the listwise deletion method resulted in a total of 35 participants for testing the second hypothesis. Inspection of the scatterplots showed the relationships among the variables to be linear, normally distributed, and there were no outliers. Several notable correlations were found, as listed in Table 14. There was a strong positive correlation between percentages of minority segregated schools and School Location's Poverty Level ($r\ (33) = .557$, $p < .01$). Word reading (WTAR), a proxy for quality of education, was found to be negatively correlated at the .05 level with percentage of minority segregated schools ($r\ (33) =-.398$, $p <. 05$). However, this negative correlation should be interpreted with caution because it does not meet the Bonferroni corrected value of .0125, and therefore, cannot be ruled as statistically significant.

Table 15.

Pearson Correlations for School Related Factors

	SLPL	% of minority Students
SLPL		
% of minority Students	.557**	
WTAR Score	-0.122	-.398*

Note: SLPL= School Location's Poverty Level; WTAR Wechsler Test of Adult Reading
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Chapter 5: Discussion

Summary of Findings

This study sought to answer two primary questions: 1) Will an adjusted regression equation yield stronger predictive ability of IQ among minorities? 2) Is there a relationship between school factors and reading level scores? The results were positive, revealing that quality of education could in fact influence the prediction of intelligence and that school-related factors, such as school racial composition and school poverty level appear to be correlated with educational quality. Although seemingly straightforward, further discussion is required to highlight the challenges and considerations associated with these findings.

The impact of quality of education, as measured by word reading level, on estimated FSIQ is grossly limited in current research and has real world implications, particularly for minorities. To address this gap in the literature, the aim was to examine the unique relationship between quality of education and estimated premorbid IQ in a non-brain injured and brain injured sample of adults. Drawing upon Wechsler's recently developed ACS comprehensive model of estimating premorbid FSIQ, namely the TOPF, the researcher examined the utility of demographic data and word reading to predict FSIQ in a sample that included Caucasians and minorities.

The first research question sought to explore whether or not a word reading score, the proxy used as an estimate of quality of education, would influence the currently used Barona regression of premorbid intelligence and, therefore, improve predictive ability of premorbid IQ, particularly among African-Americans and Hispanics. This exploration was derived from an expanding body of research indicating that quality of education is an influencing factor on overall intelligence measures (Manly et al., 2002; Smith & Welch, 1977; Glymour & Manly 2008). Capturing and measuring quality of education has not been adequately operationalized, thereby compromising the ability to predict minority premorbid cognitive abilities accurately (Campbell, Ocampo, Combs, Ford-Booker, & Dennis, 2002). Overall, the results in this study found that the inclusion did indeed improve the predictive ability of FSIQ; however, race was not a significant predictor of FSIQ. This finding is consistent with prior research showing a reduction in the predictive value of race after accounting for personal and developmental individual characteristics when predicting FSIQ (Wechsler, D., 2009).

Specifically, results showed that for the entire sample of non-brain injured and the brain injured participants, only one of the variables used in the original Barona formula approached significance in predicting WASI FSIQ: gender. Germane to the current study, gender did not emerge as a significant predictor of FSIQ after a Bonferroni correction yielding a critical p-value set to .0125. After the inclusion of quality of education, measured by word reading score, the fit of the regression model significantly improved by 18%. A rather surprising finding was that when separating the clinical and non-clinical sample, the regression variables did not perform as well as expected with the non-brain injured control group. Specifically, after running the same hierarchical regression equation for the non-brain injured control sample, the improvement of the model only approached significance after the inclusion of the reading score. In contrast, after running the same hierarchical regression for just the TBI sample, results indicated a significant improvement of the model after the contribution of the reading score (R^2 Change =. 17; $F (1, 35) = 10.10$; $p <. 001$). The results showed that the second model appeared to predict WASI FSIQ performance in TBI participants after a period of recovery of one year or more.

When attempting to explain the findings of the current study, demographic characteristics and size of the present sample ought to be considered. First, the non-brain injured control sample was small (n = 23) and may have under-powered the analysis. Thus, a possible explanation for the non-significant findings in the control sample is that it was only half the size of the clinical TBI sample. Similarly, although the sample was somewhat diverse, the sample largely comprised Caucasians (72.7%), minimizing the possible predictive ability of the race variable. Last, the mean WASI FSIQ for the clinical TBI sample (M= 102, SD = 12.75) suggest a higher functioning TBI group with perhaps less cognitive impairment, compared with TBI samples used in other studies (Perez, Schlottmann, Holloway., 1996; Martin, Donders, & Thompson., 2000; Kesler, Adams, Blasey, & Bigler, 2003). That said, after further exploratory analysis, significant group differences of WASI FSIQ scores were found between the control sample and the clinical TBI sample (see Table 16). This confirms that the brain-injured group scored lower on the WASI FSIQ than the control group, an important finding, if intellectual loss is to be implied. Interestingly, the significant prediction of obtained FSIQ when examining the effectiveness of estimated intelligence measures in a TBI population has been found in other studies (Axelrod, Vanderploeg, & Rawlings, 1999).

Table 16.

Results of t-test and Descriptive Statistics for WASI FSIQ by group

	Groups								
	Non-TBI			TBI			95% CI for Mean Difference		
	M	SD	n	M	SD	n		t	df
WASI FSIQ	113.09	11.57	23	102.30	12.75	43	-17.16, -4.41	-3.38*	64

* p < .05.

There were 23 non-TBI and 43 TBI participants. An independent-samples t-test was run to determine if there were differences in WASI FSIQ between the non- TBI control sample and the TBI clinical sample. There were no outliers in the data, as assessed by inspection of a boxplot. WASI FSIQ scores for each group were normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$), and there was homogeneity of variances, as assessed by Levene's test for equality of variances ($p = .721$). The mean WASI FSIQ was higher in the non-TBI control sample (*M* = 113.1, *SD* = 11.6) than in the TBI clinical sample (M = 102.3, SD = 12.7), a statistically significant difference, M = -10.8, 95% CI [-17.2, -4.4], $t(64) = -3.379$, $p < .01$.

An alternate explanation for the current finding in the TBI group is that word reading level is capturing an individual's quality of education, and therefore, is reflecting the individual's cognitive reserve that has been developed over time. As defined by Stern (2009), cognitive reserve is, "Individual differences in how people process tasks allow some to cope better than others with brain pathology." It could be that the higher the cognitive reserve, the better the individual is able to withstand an insult to the brain, leading to better outcomes in TBI. To support this premise, there is evidence to suggest that in the TBI population, cognitive reserve for individuals who have a higher education may reduce pre-and post-injury cognitive changes, regardless of injury severity (Kesler, Adams, Blasey, & Bigler, 2003). In the current study, the Barona regression equation alone, that included years of education, did not predict FSIQ for the brain injured clinical sample. Yet, when reading level was added, the regression model significantly improved and perhaps accounted for premorbid cognitive traits that may protect against the consequences of head injury, such as unique educational experiences. Additionally, some of the subtests used to measure FSIQ, namely Vocabulary and Matrix Reasoning have been found to be relatively resistant to a brain insult (Donders, Tulsky, & Zhu, 2001; Spreen, & Strauss, 1998) and possibly further explain the results. That said, additional investigation of cognitive reserve as a potential explanation is necessary.

The second research question sought to examine whether or not there was a relationship between school racial composition, school poverty level, and quality of education, measured by reading level. Results showed that there is a positive, significant correlation between percentage of minority students in a school and school poverty level. Further, there was a negative relationship between word reading score and percentage of minority students in the participant's elementary school. These findings are consistent with previous research concerning the current rise of residential segregation, particularly when examining the racial composition of high and low-income areas (Orfield, Kucsera, & Siegel-Hawley, 2012). Understanding relationships between social disadvantages (quality of education) and measures of intellectual ability may help the accuracy of diagnosis and improve outcomes for patients with TBI.

Limitations of this Study

Several limitations for the current study should be noted. First, other non-school variables, such as family size and health disparities, have been shown to influence disparities in cognitive performance (Condron, 2009). The current study used data that are part of a larger study, not specifically designed to assess these other variables. Thus, more research is needed to aid in determining the precise mechanisms that contribute to racial and social class disparities in cognitive test performance. Specifically, an examination of the relationships between cognitive ability and other non-school environments was not possible with the current dataset.

Second, this study was limited by the small sample size, with a small multicultural sample (minorities = 27.3%), which may have under-powered some analyses. Although the sample was large enough to detect relationships with moderate to large effect sizes, those with modest or smaller effect sizes may have not reached significance in this study. Despite this, the study benefited from having a considerable clinical TBI sample ($n = 43$).

Third, the patient sample studied was not stratified by brain injury location making it difficult to parse out any lesions that may have caused detriments in verbal areas, namely word reading. Further, for the clinical sample, this study used FSIQ at one-year or more post injury as the outcome variable. The use of this variable as a gold standard may not have been suitable. Although challenging, future studies are encouraged to use TBI patients who have had an assessment prior to their cognitive changes for comparison.

Last, this study used school-related location (i.e. city), which is less specific than zip codes. In other words, using a city to delineate poverty levels poses the risk of not accurately representing how specific neighborhoods within a city may vary. Future studies are encouraged to use more proximate measures to capture neighborhood context.

Clinical Implications of Findings

The findings in the current research have imperative clinical implications. First, the results highlight and further support the unique influences of different educational experiences on regression measures of estimated IQ. Specifically, consistent with what was found with the TOPF standardization sample, this study found that the WTAR, the proxy used for quality of education, improved predictive ability of FSIQ; however, race was not a significant predictor, supporting the premise that the well-known Black/White gap is not merely about race. Rather, it is about indirect factors such as resources and access that shape educational experiences. However, this conclusion should be tempered by the small African American/Latino sample size in the current study.

The impact of educational inequality, however, may be more salient for minority groups that are overrepresented in low-income areas. This systematic societal challenge is highlighted by current reports of an increase in the percentage of public schools in the United States with students that are poor and predominantly Black and Hispanic (U.S government and accountability office, 2016). Consistent with prior findings, the results of this study found a significant, positive correlation between the percentage of minority students in an elementary school and poverty level. Further, although not clinically significant, word reading (WTAR), a proxy for quality of education, was found to be negatively correlated with percentage of minority segregated schools. Thus, it appears that school inequality continues to be driven by trends of concentrated poverty and uneven distribution of racial groups among elementary schools. For clarity, the current results merely highlight how concentrated poverty may shape the components of schooling, such as textbooks and syllabi, teacher training, and class size (Orfield, G., Kucsera, J., & Siegel-Hawley, G. (2012) for some students living in low income areas and does not negate the fact that there are some schools in these areas that may have better outcomes.

For this reason, cognitive assessments should take into account education-related variables, such as quality of education when using measures of cognitive function. Although efforts have been made to capture differences in race and years of education in the normative standardization process of IQ tests, these variables may lack sensitivity to different educational experiences (Manly, Jacobs, Touradji, Small, & Stern, 2002). This misstep poses a risk for misattributing low-test scores to cognitive deficits, when in fact the low scores may be reflection of poor quality of education. Misdiagnosing individuals with cognitive deficits may lead to unnecessary treatment, psychological distress and financial losses (Patton, Duff, Schoenberg, Mold, Scott, & Adams, 2003; Strauss, Sherman, & Spreen, 2006). Additionally, individuals bear the consequences associated with the stereotypes and stigma of the diagnosis (Garand, Lingler, O. Conner, & Dew, 2009; Simpson, Mohr, & Redman, 2009). Therefore, comprehensively evaluating cognitive impairments by taking into account psychosocial influences, such as educational quality, may aid clinicians in effectively diagnosing and treating neuropsychological impairments in TBI.

Future Directions

Compelling studies have argued that non-school environments appear to dominate as influencing factors in producing achievement disparities (Downey et al., 2004). In particular, scholars have identified several family and health-related factors in non-school environments that impact and elucidate class disparities in learning (Condron, 2009). And finally, the location of brain injury should be taken into account in future research, when possible, in order to ascertain the differential impact on premorbid IQ estimation.

Family Size. Studies have found that living in a single parent household with a larger family size hinders academic success when compared with two-parent households (Downey, 1995; McLanahan & Sandefur, 1994). This finding may be particularly important for the working class and families that live in poor areas. Family size appears to have an impact on academic performance; therefore, another investigation may involve the examination of the influence of family-related factors on estimated IQ scores.

Health Disparities. Low income areas exhibit characteristics that lead not only to inequalities in school environments, but also to poor overall health outcomes that may inhibit learning (Williams, Priest, & Anderson, 2016). In fact, the WHO Health Commission recognized the multidimensional concept of SES as a powerful determinant of health outcomes across societies throughout the world (Marmot, Friel, Bell, Houweling, & Taylor, 2008). Moreover, residential segregation also appears to play an essential role in neighborhood quality and living conditions, including health care resources (Williams & Collins, 2001). Studies have demonstrated that health-related problems, such as hunger, poor nutrition, low birth weight and learning disabilities are often found in children situated in low income areas (Rank, 2004; Rothstein, 2004). In turn, factors that are related to poor health may consequently lead to class absences and learning disparities (Condron, 2009). For these reasons, future research should examine the influence of health-related variables on estimated IQ scores.

Brain Injury Location. One of the most common features after an acquired brain injury is a diffused axonal injury (Smith, Meaney. & Shull, 2003). This injury classification is often difficult to detect using neuroimaging techniques because of its widespread damage to white matter tracts in the brain (Smith, Meaney. & Shull, 2003). In cases where injuries are more focal, the most commonly damaged areas in the brain are the lower frontal lobes and anterior temporal areas that involve functions such as decision making, social and emotion regulation (Mattson & Levin, 1990; McDonald, Flanagan, Rollins, & Kinch, 2003). Although not as common, one study identified some language impairments in 23% of patients with head injuries (Mohr, Weiss, Caveness, Dillon, & Kistler, 1980). Given these findings, future research should stratify the clinical sample by brain injury location in order to compare reading level abilities between specific groups. This information would be useful for clinicians in their process of selecting the most appropriate technique of premorbid IQ estimation.

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