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Estimating pre-morbid intellectual functioning using the Das-Naglieri: cognitive assessment system

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ESTIMATING PRE-MORBID INTELLECTUAL FUNCTIONING USING THE DAS-NAGLIERI: COGNITIVE ASSESSMENT SYSTEM

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ABSTRACT

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Neurological evaluation often utilizes a comparison of current test performance and previous performance to note any changes in neurological functioning. Previous methods have utilized atheoretical assessment measures such as the Wechsler Intelligence Scale for Children IV as means of determining pre-morbid functioning. The purpose of this study was to develop pre-morbid intellectual functioning equations using the theoretical Das-Naglieri: Cognitive Assessment System (CAS) as a method to determine functioning prior to a neurological injury in children. Participants included the CAS standardization sample (N = 2,791). The sample was randomly divided into two groups (90% comprising the development sample and the remaining 10% consisting of the validation sample). In addition, 22 individuals from the CAS standardization sample who reported a traumatic brain injury (TBI) were also withheld for a small clinical validation sample. The development group was used to create 17 equations to estimate both CAS-Domain scores and CAS Full Scale IQ. Sixteeen of the 17 equations were accurate predictors of the CAS-Domain and CAS Full Scale scores in the non-clinical validation sample. These equations hold promise in accurate estimation in clinical samples as evidenced by the validation in the small TBI clinical sample utilized in this study although more clinical validation is required.

Key-word: pre-morbid, Cognitive Assessment System, traumatic brain injury, assessment.

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LIST OF ACRONYMS

CAS	Cognitive Assessment System
IDEA	Individuals With Disabilities Education Act
TBI	Traumatic brain injury
PASS	Planning Attention Simultaneous and Successive model
PBI	Process-Based Instruction
RTI	response to Intervention

CHAPTER I

INTRODUCTION

In the last couple of decades, researchers have begun to include the study of estimating pre-morbid intellectual functioning of people with traumatic brain injuries (TBI) into the research discipline of traumatic brain injuries. Educational researchers often searched for information regarding the magnitude of the adverse effects of brain injury and potential interventions that might be useful for children and adults to recover the loss of functioning caused by a TBI. Many studies have shown the disadvantageous effects children with TBI may face in the educational setting including difficulties in sustaining attention and concentration and other executive functioning deficits, ultimately affecting their academic performance (Semrud-Clikeman, 2001). With the increasing knowledge in understanding a person's pre-morbid intellectual functioning and how it can facilitate intervention selections, many researchers and educators alike are becoming more intrigued by what the pre-morbid estimates have to offer. Given that some degree of loss of cognitive functioning typically exists following a TBI experience, interactionists may wonder to what extent remedial efforts are successful or reorder the level and potential of the pre-injury functioning.

Traumatic Brain Injury

Traumatic brain injury (TBI) is the world-wide leading cause of death and a significant cause of disabilities in children (Suominen et al., 1998). For example, using data from 2002-2006, the Centers for Disease Control reported that approximately 511,000 cases occurred per year for children from 0-14 years of age (Faul, Xu, Wald, & Coronado, 2010). Moreover, males are more likely than females to suffer a traumatic brain injury; the ratio of injuries of males to female was approximately 2:1 between the ages of 5 and 14, with the greatest discrepancy between genders evident between the ages of 10 to 14 (Faul et al., 2010). Thus, TBI is a pervasive phenomenon in childhood.

Traumatic brain injuries are generally classified as either open or closed head injury. Open head injuries, which are rarer than closed head injuries, include wounds inflicted by gunshots, assault, and surgery (Semrud-Clikeman, 2001). In contrast, closed head injuries classically include hitting a hard surface, falling, or some types of abuse, such as Shaken Baby Syndrome (Semrud-Clikeman, 2001).

In addition to the nature (closed versus open) of head injuries, the severity of injury is also an important factor to consider and largely determines the degree of impairment of skills and abilities. The severity of injury, categorized as mild, moderate and severe, is determined by the Glasgow Coma Scale (GCS; Jennett & Teasdale, 1981), which assesses one’s level of consciousness and response.

Many studies have shown long-lasting effects of TBI for children including cognitive and neuropsychological deficits. Kaufmann, Fletcher, Levin, Miner, and Ewing-Cobbs (1993) indicated that TBI results in attentional problems, primarily in the areas of sustained and selective attention. Ewing-Cobbs, Fletcher, Levin, Iovino, and

Miner (1998) found that children with TBI displayed difficulties in their ability to focus attention, as well as sustaining and shift their attention resulting in long-lasting deficits in academic achievement. With similar samples of children with TBI, other researchers have found that these children display significant deficits in executive functioning skills such as short-term memory and problem solving skills (Dennis, Wilkinson, Koski, & Humphreys, 1995; Hoffman, Donders, & Thompson, 2000).

The reauthorization of Section 504 and the Rehabilitation Act of 1973, and the Individuals with Disabilities in Education Act (IDEA; 2004) included the category of traumatic brain injury (Russell, 1993) and is now recognized and used consistently in educational settings. Previously, most students with TBI were labeled as emotionally disturbed, learning disabled, other health impaired, or physically handicapped in order to receive services (D'Amato & Rothlisberg, 1996). The lack of a specific educational diagnosis meant less beneficial instruction for children due to the lack of a specialized education plan in schools (D'Amato & Rothlisberg, 1996).

All categories of head injuries, from mild to severe, result in a negative impact of neuropsychological and cognitive functioning including cognitive deficits, behavioral problems, poor school performance, and potentially declines in adaptive functions for more severe head injuries (Yeates, 2000). It has been reported time and again that the negative sequalae of TBI often persist well after the acute stages of recovery (Yeates et al., 2002), making knowledge of TBI applicable and necessary for educators in order for children with TBI to be successful in school.

Pre-morbid Intellectual Functioning

Researchers and educators alike are beginning to recognize the importance of comparing a child's previous level of functioning to their current cognitive functioning, or pre-morbid functioning, to detect and determine severity of the TBI (Lezak, Howieson, & Loring, 2004) and its overall adverse impact. Many studies have been conducted to find the 'best method' of estimating pre-morbid level of functioning including studies that (a) used solely demographic variables (Barona, Reynolds, & Chastain, 1984), (b) incorporated additional variables of current subtest/domain standard scores (Vanderploeg, Schinka, & Axelrod, 1996), and (c) used historical test performance data to get an accurate estimate of a person's functioning prior to the brain injury (Baade & Schoenberg, 2004).

Studies incorporating current assessment subtest and domain scores have historically used the Wechsler scales as their primary assessment including estimates using the Wechsler Adult Intelligence Scale-Revised (Vanderploeg et al., 1996), the Wechsler Adult Intelligence Scale-Third Edition (Schoenberg, Duff, Dorfman, & Adams, 2004), and the Wechsler Intelligence Scale for Children-Fourth Edition (Schoenberg, Lange, Brickell, & Saklofke, 2007). These studies utilized picture completion, information, vocabulary, and matrix reasoning as well as demographic variables of age in years, gender, and parent education level because of their demonstrated reliability and demonstrated utility in previous pre-morbid estimate equations (Schoenberg et al., 2007) such as that proposed by Barona and colleagues (1984). Demographic variables were included only if they contributed significantly to the estimation equation; all equations incorporated at least one of the demographic variables if not all into the final estimation equation. Schoenberg, Lange, Saklofske, and Suarez (2008) tested the proposed equations using a clinical sample of children who sustained a TBI and found that all variables entered into the equation assisted in yielding accurate estimates of pre-morbid functioning as compared to a healthy control sample.

The inclusion of the atheoretical Wechsler scales in the estimate of pre-morbid intellectual functioning despite its popularity in the practice of IQ assessment leaves perhaps much to be desired in view of modern theoretical, neuropsychological-based perspectives of cognitive functioning that seem more connected to remedial efforts and positive outcomes, e.g., the Das-Naglieri Cognitive Assessment System (Naglieri & Das, 1997).

Das-Naglieri: Cognitive Assessment System

The age of previous intelligence assessments, such as Wechsler and Stanford Binet scales, have not allowed for the incorporation of recent discoveries of intelligence theories into our cognitive assessments, leaving them to be dated and potentially less effective in measuring children's abilities. Naglieri and Kaufman (2001) proposed that not only are cognitive assessments such as Wechsler and Stanford Binet scales outdated, but the content of the assessments was created prior to their prospective theories of intelligence, creating assessments that were weak in theoretical basis.

An alternative conceptualization of cognitive functioning was offered by A.R. Luria (1966, 1973) who proposed that human cognitive processes involved three functional systems that work together to create mental activity or cognitive processes. Luria (1966) proposed a model of cognitive processing made up of three functional units necessary for mental activity. He went on to describe the uniqueness of each unit but also concluded that each functional unit depended on one another to function and perform effectively (Luria, 1980). Luria's work led to the conceptualization of the Planning Attention Simultaneous and Successive model (PASS; Naglieri & Das, 1990), often seen as an interactive and inter-reliant model of the construct of mental activity, which was further operationalized with the *Das-Naglieri: Cognitive Assessment System* (CAS; Naglieri & Das, 1997).

According to the authors, using the theoretical framework provided by the PASS model, the CAS surpassed the constraints experienced by previous intelligence tests (Naglieri & Kaufman, 2001). The benefit of the PASS model over traditional models of intelligence was the incorporation of planning and attention domains, the two areas considered to be essential for cognitive functioning (Naglieri & Das, 1997). The CAS proposed to replace the term *intelligence* with mental abilities being referred to as *cognitive processes* (Naglieri, 1999).

Thus, with the PASS model as a foundation, Naglieri and Das (1997) created a new assessment of cognitive processes that was comprised of four domains (Planning, Attention, Simultaneous, and Successive). The four domains also contributed and formed a psychometric estimate of a Full Scale score. The CAS standard battery has 12 subtests with three subtests factoring into each of the PASS domain scores. The subtests of the CAS are Planning Scale--Planned Codes (PCd), Matching Numbers (MN), Planned Connections (PCn); Attention Scale--Number Detection (ND), Expressive Attention (EA), Receptive Attention (RA); Simultaneous Scale--Figure Memory (SR), Nonverbal Matrices (NvM), Verbal-Spatial Relations (VSR); Successive Scale--Sentence Repetition (SR),Word Series (WS), Speech Rate (SpR) [children aged 5 to 7 years only], and

Sentence Questions (SQ) [children aged 8 to 17 years only]. (For a more detailed description of the Cognitive Assessment System, reference Chapter III. Methodology: The *Das-Naglieri Cognitive Assessment System*)

Statement of the Problem

The practice of estimating pre-morbid intellectual functioning on school-aged children has many utilities including, but not limited to, determination of brain injury severity, assistance with intervention selections in the school, and future outcomes for affected children. Few studies exist in estimating pre-morbid intellectual functioning in school aged children, with current studies relying heavily on the Wechsler intelligence assessments such as the Wechsler Intelligence Scale Children III/IV (WISC III/IV) and the Wechsler Adult Intelligence Scale III (WAIS III). The reality that only one set of equations stands out among the rest and is available for use with children, whose center intelligence assessment lacks the sensitivity to detect subtle deficits in this population (Naglieri, Das, & Jarman, 1990), is being used to ascertain information about a child's outcome is concerning. Due to the theoretical limitations of the Wechsler scales, the inclusion of an assessment involving cognitive processes, such as the Cognitive Assessment System, should be considered in estimating pre-morbid intellectual functioning.

The Purpose and Rationale of the Study

With traumatic brain injuries (TBI) remaining one of the main public health problems in both developed and developing countries and the leading cause of brain damage in children and young adults (Lezak et al., 2004), the need for a more comprehensive understanding of estimating pre-morbid, that is pre-injury intellectual functioning for school aged children who have suffered a TBI, is crucial. Schools and clinics are faced with an increasing demand to provide accommodations and interventions for children with a TBI diagnosis, and the ability to estimate pre-morbid intellectual functioning is essential in the determination of services. The CAS (Naglieri & Das, 1997) has linked assessment findings with interventions for children (e.g., Carlson & Das, 1997; Naglieri & Gottling, 1995, 1997), making it a viable and necessary addition to the field of estimating pre-morbid intellectual functioning.

This study's purpose was to create an equation(s) that utilizes an assessment whose foundations center on a neuropsychological theory of cognitive processing, whose creation was theoretically driven, and has research linking assessment data to interventions. In addition, creating an equation(s) that expands from the already created pre-morbid intellectual functioning equations, such as the OPIE III for adults or the equations using WISC IV standardization data, whose basis lies in almost century old theories and practices will benefit both educators and practitioners in estimating pre-morbid intellectual functioning.

The rationale and need for the present study was based on the following points supported by the literature including

1. The limited number of assessments and equations that are available for use in estimating pre-morbid intellectual functioning.
2. The lack of neurologically based intelligence theories in other intellectual assessments used to estimate pre-morbid intellectual functioning.
3. The need for further exploration and validation of the technique of estimating pre-morbid intellectual functioning in school aged children.

4. The need to expand previous research done in estimating pre-morbid intellectual functioning.

Research Questions

Based upon the previous discussion and the comprehensive literature review in Chapter II (see next), the following research questions were investigated.

Q1 Which of the Planning domain subtests (Matching Numbers, Planned Codes, Planned Connections), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Planning Domain?

Q2 Which of the Attention domain subtests (Expressive Attention, Number Detection, Receptive Attention), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Attention Domain?

Q3 Which of the Simultaneous domain subtests (Nonverbal Matrices, Verbal-Spatial Relations, Figure Memory), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Simultaneous Domain?

Q4 Which of the Successive domain subtests (Word Series, Sentence Repetition, Sentence Questions, Speech Rate), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Successive Domain?

Q5 Which of the Cognitive Assessment System 12 *subtests*, in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Full Scale score?

Q6 Which of the Cognitive Assessment System four *domains* (Planning, Attention, Simultaneous, Successive), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Full Scale score?

Q7 Using a subsample of children with TBI and the withheld 10% from each age group, will the equations prove valid in estimating pre-morbid intellectual processing?

Limitations of the Study

One limitation of the current study was the finding that children's cognitive skills can progress rapidly during the first six months following a neuropsychological insult (Dykeman, 2009); thus, the chance of either over- or under-estimating the child's pre-morbid intellectual functioning increases as the time since injury elapses (Schoenberg et al., 2008). This limitation was further expressed by the lack of time-elapsed since injury data of the 22 individuals in the CAS sample with a recorded TBI furthering the need for additional studies to validate the equations with children who have experienced a TBI.

Another limitation of the current study was that the developed equation(s) was not able to account for all variables that might impact the variance in an individual's PASS cognitive processes and overall cognition, e.g., location of injury, time elapsed since injury, and severity of injury (Schoenberg et al., 2008; Harrington, 1990). Again, this could have resulted in an over- or under-estimation of the child's pre-morbid intellectual functioning and should be considered when interpreting the results from the equation(s).

Given the limited size of the TBI validation sample for the pre-morbid intellectual estimation equation(s), additional research might be necessary to establish the clinical utility of the equation(s) on children with traumatic brain injury. Additional studies might be warranted to validate the equation(s) with children who have suffered other neuropsychological injuries.

Definitions of Terms

Closed head injury. The most common of head injuries, closed head injuries usually result from falling, automobile accidence or assaults. Head injuries can occur at the site of impact (coup) or the opposite site of impact (countercoup injury). Symptoms of closed head injuries often include hypoxia, increased intracranial pressure, shock, seizures, and sometimes infections.

Executive functioning. The function that allows us to organize our behavior over time, plan and organize activities, manage our emotions, and regulate our thoughts in order to work in a more efficient and effective manner (Dawson & Guare, 2010)

Glasgow coma score (GCS). A very quick, bedside assessment for doctors to determine level of consciousness and brief assess of possible impairment. The quick assessment results in a score that is based on a scale from 3-15.

Mild head injury. An injury to the head that results in loss of consciousness or post amnesia for less than one hour with a GCS between 13 and 15.

Moderate head injury. An injury to the head that results either loss of consciousness or amnesia for 1 to 24 hours post-accident, with a GCS between 9 and 12.

Open head injury. Rarer than closed head injuries, they typically include wounds inflicted by gunshots, assault, and surgery (Semrud-Clikeman, 2001)

PASS. Planning--a cognitive process that uses organization and monitoring that is designed to apply and evaluate problem solving (Naglieri & Das, 1997). Attention--cognitive process involving selectively focusing on a given stimuli while inhibiting the response to focus on other stimuli (Naglieri & Das, 1997). Simultaneous processing--a cognitive process that integrates stimuli into synchronous and primarily spatial groups.

(Naglieri & Das, 1990). Successive processing--a cognitive process that involves the integration of stimuli into some sort of specific series where the elements create a chain-like effect (Naglieri & Das, 1990).

Pre-morbid. Preceding the occurrence of brain injury or disease.

Severe head injury. An injury/insult to the head that results in loss of consciousness and/or amnesia that lasts longer than 24 hours post-accident, with a GCS between 3 and 8.

Traumatic brain injury. As defined by U.S. Department of Education (1992):

> an acquired injury to the brain caused by an external physical force, resulting in total or partial functional disability or psychosocial impairment, or both, that adversely affects a child's educational performance. The term applies to open or closed head injuries resulting in impairments in one or more areas, such as cognition; language; memory; attention; reasoning; abstract thinking; judgement; problem-solving; sensory, perceptual, and motor abilities; psycho-social behaviour; physical functions; information processing; and speech. The term does not apply to brain injuries that are congenital or degenerative, or to brain injuries induced by birth trauma. (pp. 44, 802)

Working memory. The process of holding information for the purpose of completing a task and includes both the storage and manipulation of information (Levin et al., 2004).

CHAPTER II

REVIEW OF LITERATURE

The overwhelming number of children experiencing a traumatic brain injury (TBI; Faul et al., 2010) necessitates the need for an additional method of estimating pre-morbid intellectual functioning that goes beyond demographic variables, theoretically outdated general ability measures of intelligence (e.g., Wechsler scales), and academic achievement variables.

This chapter provides an introduction to the history and theories of intelligence used to estimate pre-morbid intellectual functioning including the cognitive processing theory that served as the foundation for the development of processing the Cognitive Assessment System (CAS) uses. Then definitions and classifications of traumatic brain injury and its educational impact in students in kindergarten through twelfth grade are reviewed. This chapter discusses this in light of current methods of estimating pre-morbid intellectual functioning, focusing on alternative theories and methods of estimating pre-morbid functioning that necessitated the current study.

Brief History of Intelligence Theory and Testing

The field of intelligence testing was initiated in 1905 with the introduction of Alfred Binet and Theodore Simon’s intelligence test. Binet’s theory of intelligence subscribed to intelligence as a single construct, consistent with the thinking of the time of theorists positing “intelligence” rather than multiple, or distinct, abilities making up the larger idea of “intelligence” (Kamphaus, 1993). Alfred Binet’s scale of intelligence was constructed for the sole purpose of diagnosing mental retardation (Kamphaus, 1993).

Unlike Alfred Binet’s single entity theory of intelligence, Charles Spearman’s (1927) introduced his theory of general intelligence or what he called “g.” Spearman’s theory of intelligence came after Binet’s theory, resulting from a significant amount of factor analysis to determine that intelligence is comprised of many distinct abilities. Spearman’s “g” theory is ranked above other hierarchical theories of intelligence where there is an overall construct that is made up of many specific “s” factors. Spearman suggested that “g” was the underlying mental energy necessary to all cognitive problem-solving (Kamphaus, 1993).

Wechsler (1958) viewed intelligence as a complex interaction of facilities that produced intelligent behavior that reflected upon Spearman’s “g”. Wechsler expanded upon Spearman’s theory and suggested that intelligence is not localized in one area of the brain and thus focused on what he termed the “perception of relations.” His perception of relations implied that representation of stimuli in terms of their location in neurons was unimportant and was independent of the localization of a specific stimulus. During test construction, Wechsler borrowed ideas of methods and tests from the Army mental testing program that assessed incoming adults in the military during World War I to determine appropriate placement based on aptitude (Naglieri & Kaufman, 2001).

Some argue that many intelligence theories and tests have not changed since the original production of the Binet and Simon scale from 1905 and David Wechsler’s first IQ test published in 1939. For example, Naglieri and Kaufman (2001) compared the old to the new versions of the Stanford-Binet and Wechsler scales as essentially a cosmetic facelift, having identical constructs with modifications only in presentation and updates in standardization data. The problem with having only a cosmetic facelift was the data obtained from these assessments might reflect current census data and population but were still an atheoretical assessment that might not measure what it is now purporting to measure. Thus, these tests have not been updated to include the copious amounts of contemporary research findings even during the past 50 years. Nonetheless, the assessments are essentially still considered effective in measuring what they originally purported to measure (Kamphaus, 1993) and remain popular.

Starting in the 1960s, the “cognitive revolution” (Miller, Galanter, & Pribram, 1960) encouraged researchers and clinicians to examine intelligence from a different perspective in terms of cognitive processes rather than “g” or global ability (Naglieri & Kaufman, 2001). Construing intelligence in terms of cognitive processes allowed for the introduction of the Kaufman intelligence tests in the 1980s, e.g., the Kaufman Assessment Battery for Children (K-ABC), the Differential Ability Scales (DAS; Elliot, 1990), and Das-Naglieri: Cognitive Assessment System (Naglieri & Das, 1997) in the 1990s.

Luria’s Theory of Mental Processes and the Planning Attention Simultaneous and Successive Model

A comprehensive overview of Luria’s (1966, 1973) model of cognitive processing including the Planning Attention Simultaneous and Successive (PASS) model is discussed in the following section, followed by a brief introduction to the Das-Naglieri: Cognitive Assessment System and its link to evidence based interventions through assessment results.

Luria’s (1966, 1973) Planning Attention Simultaneous and Successive (PASS) model proposed that human cognitive processes involved three functional systems that worked together and were essential for mental activity. Luria (1973) believed that the three functional systems were housed in different neuroanatomical areas, contributed uniquely to mental processes, and worked together to create mental activity. Luria further suggested that these areas were interdependent such that each functional unit depended on the other units to function and perform effectively (Luria, 1980).

The first functional unit of Luria’s (1973) model is responsible for regulating cortical tone, or arousal, which allows for the focus and maintenance of attention. The second functional unit receives and stores information using both simultaneous and successive processing once information is received. The third functional unit is the planning or decision making unit, which regulates and directs mental activity. In the sections that follow, the functional units proposed by A.R. Luria in detail as well as the PASS model constructs supported by Luria’s model are described.

Attention

The first functional unit has the responsibility of maintaining arousal and cortical stimulation, allowing a person to maintain a certain level of attention (Luria, 1973). The areas of the brain that contribute to this function include the brain stem, diencephalon, and medial areas of the brain. Luria proposed that a deficit in the first functional unit, through inadequate or excessive performance, could produce problematic functioning of the second and third functional units.

Attention is the main component of the first functional unit and is included in the PASS model as an essential mental process. Wechsler scales and other intelligence tests have been criticized as either not including measures of attention or not properly measuring attention in intelligence tests (Naglieri & Das, 1988). Given that attention is frequently construed as a key component of academic achievement and one of the underlying symptoms of a TBI (Semrud-Clikeman, 2001), it is important to assess attention to further understand how it can affect the performance of other mental processing structures.

Consistent with this, Gutentag, Naglieri, and Yeates (1998) investigated observed differences in test scores of children with mild, moderate, and severe TBI compared to healthy peers matched on critical variables. They hypothesized that children with TBI would have lower performance on Attention and Planning subtests compared to other subtests. Results indicated that children with TBI scored similarly to their peers with only one Attention subtest (Number Detection) resulting in significant differences and scored significantly different on all three Planning Subtests (Matching Numbers, Planned Codes, Planned Connection). These differences suggested that children with TBI performed differently on attention and planning tests compared to control, or normal, children.

Successive and Simultaneous Processing

The second functional unit is responsible for how a person receives incoming information, how they process that information, and how they preserve the incoming information. This area of functioning is located in the occipital, parietal, and temporal lobes (Luria, 1973)--the areas of the brain that are responsible in part for decoding and storing sensory information. Luria (1966) proposed that there are two approaches the human brain uses to process information: simultaneously and successively. The two methods of simultaneous and successive processing are discussed below.

Simultaneous processing is similar to categorizing--where the brain integrates stimuli perceived from groups, determines the relationship among the stimuli, and acts accordingly (Naglieri & Das, 1990). Simultaneous processing may be used to follow a multi-step direction of “put the placemat under the plate but to the left of the napkin.” Simultaneous processing requires that one consider a larger context and thus likely requires planning and attention in this task. Successive processing allows the integration of stimuli through the use of linear relationships to form a string of stimuli (Naglieri & Das, 1990). For example, successive processing is necessary in following a storyline and being able to understand the progression of the story from beginning to end.

Gutentag et al. (1998) tested these elements and demonstrated that when children with TBI were compared to a control group matched on critical variables, their scores did not differ significantly from one another on all Simultaneous subtests (Nonverbal Matrices, Verbal-Spatial Relations and Figure Memory) and all but one Successive subtests (Word Series and Sentence Questions). The Sentence Repetition subtest from the Successive domain was the only one to demonstrate significant differences between normal and TBI children.

Planning

The third and final functional unit from Luria’s mental processing model is located in the frontal and pre-frontal areas of the brain. Luria (1973) proposed that the third unit was implicated in executive functioning or the ability to plan, act on said plan, and evaluate the plan afterwards. Das, Naglieri and Kirby (1994) described the third functional unit as the one that joined the three units and produced mental activities. Das

(1984) further suggested that the third functional unit makes human intelligence what it is.

The final functional unit allows for the Planning in the PASS model to occur. Without the executive function, or the ability to plan, execute, and evaluate said plan, other mental processes might not be acknowledged because planning in essence links Attention, Successive, and Simultaneous processing together. However, just as attention has been largely overlooked in measures of intelligence, Naglieri and Das (1988) contended that planning has also generally been ignored. In particular, planning is not typically measured directly through intelligence assessments but rather through clinical observations or third party behavior rating scales such as the Behavior Rating Inventory of Executive Functioning (BRIEF; Gioia, Isquith, Guy, & Kenworthy, 2000).

Planning is an essential component in academic areas and is important in self-monitoring, impulse control, and initiating task completion (Naglieri, 1999). It is important to include measures assessing planning processes in children with TBI as they are often observed having trouble with impulse control and executive functioning (Semrud-Clikeman, 2001). Gutentag et al. (1998) reported that children with TBI earned lower scores on subtests from the Planning domain compared to healthy controls.

The Das-Naglieri: Cognitive Assessment System

With the PASS model as a foundation, Naglieri and Das (1997) created an assessment of cognitive processes for children aged 5 through 17 that was comprised of four domains (Planning, Attention, Simultaneous, and Successive) and also an overall Full Scale score, a psychometric for practical purposes. The Cognitive Assessment System (CAS) standard battery has 12 subtests with three subtests factoring into each of the PASS domain scores. The subtests of the CAS are Planning Scale--Planned Codes (PCd), Matching Numbers (MN), Planned Connections (PCn); Attention Scale--Number Detection (ND), Expressive Attention (EA), Receptive Attention (RA); Simultaneous Scale--Figure Memory (SR), Nonverbal Matrices (NvM), Verbal-Spatial Relations (VSR); and Successive Scale--Sentence Repetition (SR),Word Series (WS), Speech Rate (SpR) [children aged 5 to 7 years only], and Sentence Questions (SQ) [children aged 8 to 17 years only]. (For a more detailed description of the Cognitive Assessment System, see Chapter III. Methodology: The Das-Naglieri Cognitive Assessment System)

The PASS theory served as the foundation for a number of proposed interventions. One such intervention was the Process-Based Instruction (PBI; Ashman & Conway, 1993). Process-Based Instruction provides valuable information on how to incorporate planning instruction into everyday activities in the classroom. It has the potential to tie the CAS test data to an effective classroom intervention tailored to the specific needs of the student.

Linked to the PBI intervention are studies that have focused on encouraging children’s use of planning and have shown positive effects on their academic performance. For example, Cormier, Carlson and Das (1990) sought to facilitate planning rather than teach planning through direct instruction by tying verbalization techniques to planning, which resulted in an increase in performance. Other studies (e.g., Carlson & Das, 1997; Naglieri & Gottling, 1995, 1997), including one involve math computation, have likewise sought to facilitate planning through means other than direct instruction.

Naglieri and Gottling (1997) examined whether a math intervention emphasizing planning would differentiate among groups depending on cognitive characteristics displayed by students. All students were administered the CAS though protocols were not scored until the study was completed. Results indicated that children who had low Planning scores benefited from the planning instruction more than did students high in Planning (Naglieri & Gottling, 1997). Thus, matching intervention and instruction based on cognitive weaknesses displayed by students resulted in outcomes that were beneficial not only children for with TBI but all students. However, given that this project primarily focused on children with TBI, in the next section classification and symptoms of such injuries are reviewed.

Definition, Classification and Symptoms of Traumatic Brain Injury

Traumatic brain injury can manifest itself in many different ways depending on how it is defined, the classification of the injury, and the symptoms one experiences following a traumatic brain injury. In this section, a definition commonly used by educators is presented, followed by a discussion of the classification of TBI. The section concludes with an overview of the symptoms commonly experienced following a TBI.

Definition of Traumatic Brain Injury

The field of education has recognized traumatic brain injury (TBI) as an educational diagnosis that can result in special education services or individualized interventions since IDEA in 1990 and its revision in 2004. Definitions of traumatic brain injury vary; however, the one used by educational institutions is the definition provided by the U.S. Department of Education (1992):

> Traumatic Brain Injury means an acquired injury to the brain caused by an external physical force, resulting in total or partial functional disability or psychosocial impairment, or both, that adversely affects a child's educational performance. The term applies to open or closed head injuries resulting in

> impairments in one or more areas, such as cognition; language; memory; attention; reasoning; abstract thinking; judgment; problem-solving; sensory, perceptual, and motor abilities; psycho-social behavior; physical functions; information processing; and speech. The term does not apply to brain injuries that are congenital or degenerative, or to brain injuries induced by birth trauma. (pp. 44, 802)

Classification of Traumatic Brain Injury

Traumatic brain injuries are often classified as open or closed head injuries and also are described in the terms of the severity, which include mild, moderate, or severe levels. The classification of open versus closed as well as the severity of the injury provides valuable insight into the general prognosis and guides the choice of intervention for children who suffered from a TBI.

The severity of injury has been correlated with difficulties in visual attention, verbal memory, performance (non-verbal) IQ, academic performance, and adaptive behavior (Ewing-Cobbs et al., 1997). In addition, DiScala, Osberg, Gans, Chin, and Grant (1991) found that approximately 20-40% of TBI classified as severe resulted in impairments that affected learning and development. One important distinction that should be noted is that injuries that stem from infections, tumors, metabolic disorders, toxins, and anoxic injuries are not considered TBI but rather are considered non-traumatic brain injuries (Savage & Wolcott, 1994); thus, they were not included in the description of TBI for this study.

The timing and the nature of the injury (open versus closed) might have consequences that are not evident during childhood. However, it should be noted that the manifestation of symptoms from a TBI in childhood is often delayed because of the disruption of general cognitive and behavioral development that can result from a head injury (Lehr, 1990; Russell, 1993). Thus, although not always apparent, the trauma itself can disrupt the normal cognitive development experienced during childhood and adolescence (Haley, Cioffi, Lewis, & Barya, 1990).

General Symptoms of Traumatic Brain Injury

A number of researchers and theorists have suggested that specific attentional and processing components are impaired following a TBI (Mirsky, 1996; Ponsford & Kinsella, 1992; Posner & Peterson, 1990; Stuss et al., 1989; van Zomeren & Brouwer, 1994) including sustained attention, selective attention, and speed of processing. “Response variability,” defined as high levels of variability and fluctuation in performance, is also a symptom of TBI (Catroppa & Anderson, 1999; Mirskey, 1996; Stuss et al., 1989; van Zomeren & Brouwer, 1994).

Educational Impact for Children with Traumatic Brain Injuries

It is common for children who experience a TBI to have difficulties when returning to school because of the effects the TBI has on overall functioning (Hawley, Ward, Magnay, & Mychalkiw, 2004). Classification of TBI in the schools should be less challenging as educators become more aware of the symptoms and challenges children with TBI face. Classification of TBI in the schools including important information to ensure an appropriate placement for children with TBI is first discussed, followed by a discussion on the symptoms of TBI by the varying levels of severity commonly seen in schools and how it impacts the child’s ability to pay attention, retain information, and learn in the classroom.

Classification of Traumatic Brain Injury in the Schools

At the very least, 1 out of every 550 students (school-aged) will experience some form of TBI every year that can result in a long-term disability (Savage & Wolcott, 1994). Further, it is estimated that at least 20 students out of 10,000 will sustain a TBI and require educational support (Arroyos-Jurado, Paulsen, Merrell, Lindgren, & Max, 2000). Hux, Marquardt, Skinner, and Bond (1999) found that nearly 29% of students with a reported TBI received special education services and that younger children received more special education services. Hux et al. suggested that this occurred because educators were better able to identify and diagnose academic, social, and behavior challenges in younger students than in older students.

Although TBI can significantly impact educational outcomes in children, educators with minimal training and exposure to TBI express apprehension in understanding and accommodating a child with TBI (Blosser & DePompei, 1991). In addition, educators and parents might not understand that a diagnosis of mild TBI does not imply that educational outcomes are also mild. That is, even a mild TBI diagnosis might be associated with significant and continuing adverse consequences for learning (Dikmen & Levin, 1993; Savage, 1991). However, mistakenly assuming that mild TBI is synonymous with mild impact in educational functioning might not allow the student access to interventions and resources essential in their recovery.

It is common for children with TBI to be classified as necessitating special education services while in school. The degree of services provided, including interventions in the general education setting or placement in special education classrooms, depends entirely upon the individual case and the knowledge of the professionals involved. Typically, when a student is identified with an educational disability such as a learning disability or emotional disability, they undergo annual or triennial evaluations to determine if services are still needed and to adjust services received as appropriate. Children with TBI require more frequent evaluation (e.g., monthly or after every grading period) that depend on the individual case (Cohen, 1986; Lehr, 1990). Frequent evaluation is common in the recently proposed model of Response to Intervention (RTI) within IDEA (2004) and is helpful in providing the students with the necessary resources as educators become aware of the student's need.

Educational Impact and Level of Severity

Mild TBI may result in significant educational problems. For example, Levin et al. (2008) found that children with mild TBI showed a decrease in working memory abilities compared to non-injured children. These results indicated that some deficits in executive functioning, particularly working memory, might exist for children with mild TBI. Children who suffer a moderate TBI generally display executive functioning deficits including problems with purposeful, goal-directed, and problem solving behavior (Gioia & Isquith, 2004). In addition to problem solving, deficits are generally evident in domains such as attention/concentration and memory (Rimel, Giordani, Barth, & Jane, 1982).

Severe TBI can have drastic consequences for children, especially with regard to their academic successes and future outcomes. Severe head injuries are critical; 50% of children admitted into hospitals die due to a severe head injury (Fletcher et al., 1995). Those who survive have long-lasting deficits in educational achievement (Ewing-Cobbs, Fletcher, & Levin, 1986; Ewing-Cobbs, Iovino, Fletcher, Miner, & Levin, 1991) and display significant deficits in executive functioning skills such as attention/concentration, memory, and problem solving (Jaffe, Polissar, Fay, & Liao, 1995).

Academic Problems of Children with Traumatic Brain Injury

The inability to sustain attention in the classroom results in a decrease in working memory, leaving some students with TBI at a loss compared to their peers. With problems in attention/concentration and working memory, children often get frustrated, potentially resulting in behavioral problems. Studies have found a significant relationship between head injury and hyperactivity (Bijur, Haslum & Golding, 1990) as well as difficulties in attention and low frustration tolerance up to four years after the injury (Klonoff, Low, & Clark, 1977). Problems with attention, organization, and self-regulation can also impact the child's ability to read, write, and perform basic math functions (Fay et al., 1994).

Schaffer, Bijur, Chadwick, and Rutter (1980) reported that one-third of the children sampled were reading at a level greater than or equal to two years below their chronological age. They proposed that the decline in reading ability was facilitated by a global loss of intellectual functioning. This hypothesis was later refuted by Slater and Kohr's (1989) and Berger-Gross and Schackelford's (1985) findings showing arithmetic problems persisted more than spelling and writing activities despite intellectual (IQ) recovery.

Hawley et al. (2004) reported similar results when they assessed academic and educational impact on 130 children with TBI aged 5 through 15. They found that teachers reported that children who suffered a mild or moderate TBI had difficulties in attention/concentration, memory, and problems with school work. As well, 94.4% of children with reported memory problems experienced trouble with school work. Reading ability was also measured on 36 students with TBI using the Wechsler Objective Reading Dimensions (WORD) and was analyzed to determine the discrepancy between chronological age and reading age. Approximately 52% of the individuals assessed read at a level greater than or equal to one year below their chronological age and 36.1% of students read at a level greater than or equal to two years below their chronological age. However, it was unclear whether there were reading concerns for these students prior to injury. These results illustrate that academic and educational problems might persist despite the appearance of intellectual recovery.

Catroppa and Anderson (1999) synthesized the research of TBI and its effect on academic performance in children in their comprehensive study of academic skills, examining listening comprehension, reading, spelling, and arithmetic in 69 children who had sustained a documented mild, moderate, or severe TBI. Importantly, unlike prior studies, the researchers analyzed pre- and post-injury data and found no significant differences between groups on pre-injury ability. Pre-injury data used in the study consisted of parent report post-accident reflecting on previous functioning of their child.

Catroppa and Anderson (1999) results indicated that children suffering a mild TBI fared better than children experiencing a moderate or severe TBI. In the areas of spelling and reading, children with moderate and severe TBI performed similarly. In contrast, for arithmetic and listening comprehension, a “dose-response relationship” was clear, such that as the severity of a head injury worsened, the student’s performance on these tasks became commensurately worse. Further, it appeared that individuals with severe TBI did not improve at the 12 month and 24 month post-injury evaluation in the area of arithmetic

(Catroppa & Anderson, 1999). Such data highlight the value of having a measure of pre-morbid intellectual functioning so as to assess pre and post head injury performance.

The growing numbers of children who suffer a traumatic brain injury (TBI) enrolled in schools increase the need for education professionals to be aware of not only symptoms of TBI but also well-versed in effective interventions to help students with TBI succeed academically. Similarly, considering the long-lasting deficits of TBI, it is also important for educators to take into account not on current possible deficits but also how children functioned prior to the injury so that interventions and proper educational arrangements can be made that best suit the individual. A vital way to assess pre-morbid functioning and create effective interventions would be to use cognitive assessment measures linked to interventions through demonstrated research studies.

Pre-morbid Intellectual Functioning

Pre-morbid intellectual functioning, or the level of functioning prior to an insult or injury to the brain, is valuable in determining the direct impact of the TBI and future directions for interventions and supports for the individual. Typically, clinicians estimate pre-morbid intellectual functioning because it provides a baseline in establishing the presence and magnitude of deficits that result from brain injury. Additionally, estimating pre-morbid functioning can be helpful for educators to select appropriate interventions and adjust progress monitoring measures to continually assess a child's functioning.

A variety of methods are used to estimate pre-morbid intellectual functioning including (a) clinical interview, (b) demographic regression formulas, (c) current test performance regression formulas, (d) combining demographic and current performance data, (e) historical test performance, and (f) combining historical test performance with demographic data. Determining appropriate methods for estimating pre-morbid intellectual functioning can be difficult. Measures used should strongly correlate with the measured IQ of a healthy individual and must be resistant to neurological deficit and/or psychiatric disorder (Morris, Wilson, Dunn, & Teasdale, 2005). Each of the methods of estimating pre-morbid intellectual functioning is described in the following sections.

Clinical Interview

Clinical interviews are one of the most common and least accurate methods of estimating pre-morbid intellectual functioning. For example, Smith-Seemiller, Franzen, Burgess, and Prieto (1997) investigated the method of pre-morbid estimation neuropsychologists used in their clinical practices. They found that the most commonly used method of estimating was the clinical interview, followed by the Barona et al. (1984) equation that utilized demographic information in a regression model to estimate pre-morbid intellectual functioning. Such findings are problematic, however, given that a number of studies (see Kareken & Williams, 1994; Wedding & Faust, 1989) have demonstrated it to be largely ineffective due to its subjective nature.

Many variables account for the subjectivity of the clinical interview to estimate pre-morbid intellectual functioning for clinical populations, e.g., a client’s possible exaggeration of his/her difficulties (Johnson-Greene & Binder, 1995). Even assuming that records are available, increasing the accuracy of information provided to a clinician, clinical judgment remains subjective and reaching proficiency (i.e., accuracy) is extremely difficult (Kareken & Williams, 1994). Romans and Caplan (1994) found that clinical judgment, or subjective estimates, did not take into account client education and occupation levels despite their known influence on assessment performance and results.

Demographic Information

Another method in estimating pre-morbid intellectual functioning, and possibly more highly regarded than clinical interview, is to use demographic information in a regression formula to estimate previous levels of functioning in clients who have suffered a TBI. Barona et al. (1984) were the first to develop an actuarial method of estimating pre-morbid functioning; they created an equation that was more objective than interviews and more culturally sensitive than other methods.

Barona et al. (1984) developed their equation by using the standardization sample from the Wechsler Adult Intelligence Scale-Revised in combination with seven demographic variables: age, sex, education, occupation, urban-rural setting, geographic region of residence, and race. Results indicated that race, education, and occupation were the most powerful predictors for all equations created because they tended to load onto the equation more than the other variables used in the analysis.

Three equations were created using this information to estimate pre-morbid: Full Scale IQ, Verbal IQ, and Performance IQ. Equation 1 gives the formula for Estimated Verbal IQ:

$$\text{Estimated Verbal IQ} = 54.23 + .49\,(\text{age}) + 1.92(\text{sex}) + 4.24\,(\text{race}) + 5.25\,(\text{education}) + 1.89\,(\text{occupation}) + 1.24\,(\text{U-R residence}) \quad (1)$$

with a standard error for the estimate of VIQ = 11.79, *R*=.62. For example, using the codes provided by Barona et al. (1984), a 25-34 year old (coded 4) Black (coded 1) female (coded 1) with 16 or more years of education (coded 6) and a professional job (coded 6) in an urban setting (coded 2) would have an Estimated Verbal IQ of 107.67, using Equation 1 as follows: 54.23 + .49(4) + 1.92(1) + 4.24(1) + 5.25(6) + 1.89(6) + 1.24 (2) = 107.67.

Equation 2, taken from Barona et al. (1984), gives the formula for Estimated Performance IQ:

$$\text{Estimated Performance IQ} = 61.58 + .31\ (\text{age}) + 1.09\ (\text{sex}) + 4.95\ (\text{race}) + 3.75\ (\text{education}) + 1.54\ (\text{occupation}) + .82\ (\text{region}) \tag{2}$$

with a standard error for the estimate of PIQ = 13.23, R =.49. For example, using the same coding described previously, with the exception that the North-Central region (coded 2) is implemented rather than U-R residence, the Estimated Performance IQ would be 102.24, using Equation 2 as follows: 61.58 + .31 (4) + 1.09 (1) + 4.95 (1) + 3.75 (6) + 1.54 (6) + .82 (2) = 102.24.

Equation 3, taken from Barona et al. (1984), gives the formula for Estimated Performance IQ:

$$\text{Estimated Full Scale IQ} = 54.96 + .47\ (\text{age}) + 1.76\ (\text{sex}) + 4.71\ (\text{race}) + 5.02\ (\text{education}) + 1.89\ (\text{occupation}) + .59\ (\text{region}) \tag{3}$$

with a standard error for FSIQ = 12.14, R = .60. For example, using the same coding described previously in illustrating Equation 2, the Estimated Full Scale IQ would be 105.59, using Equation 3 as follows: 54.96 + .47(4) + 1.76 (1) + 4.71 (1) + 5.02 (6) + 1.89 (6) + .59 (2) = 105.59.

Overall, the greatest weights in each of the equations were given to education, occupation, and race, suggesting that these variables were the strongest predictors of pre-morbid intellectual functioning. However, occupation and education level were not practical when estimating pre-morbid intellectual functioning in children, necessitating that other variables be used.

A number of other researchers have examined demographic variables as predictors of pre-morbid functioning. For example, Heaton, Taylor, and Manly (2003) found, similar to Barona et al. (1984), that variables such as education, ethnicity, and gender all affected neuropsychological test performance in normal adults. Other researchers have shown education, ethnicity, and gender affected performance in diverse clinical samples (Moses, Pritchard, & Adams, 1999; Vanderploeg, Axelrod, Sherer, Scott, & Adams, 1997).

However, there are potential limitations to only using demographic variables in estimating pre-morbid intellectual functioning. Basso, Bornstein, Roper, and McCoy (2000), among other researchers, found that the Barona equation (both the original and the revised) was susceptible to regression towards the mean and was likely to overestimate pre-morbid functioning for individuals at the lower end of functioning and underestimate pre-morbid functioning for individuals at the higher end of cognitive functioning (see also Paolo, Ryan, Troster, & Hilmer, 1996; Veiel & Koopman, 2001; Wrobel & Wrobel, 1996). Sweet, Moberg, and Tovian (1990) likewise reported that the Barona equation was less valid at the upper and lower extremes of ability.

Current Test Performance

Another method of estimating pre-morbid intellectual functioning is using a client’s current test performance. This method has been applied using assessments such as the Wechsler Adult Intelligence Scales (WAIS-R through WAIS-IV), the Wechsler Test of Adult Reading (WTAR), or the North American Reading Test (NART). This method is based on the assumption that some test scores are less likely to be affected than others following a neurological insult (Baade, Heinrichs, Coady, & Stropes, 2011). Baade and colleagues (2011) labeled tests less likely to be affected by neurological insult as “hold tests,” while those that are more susceptible to injury as “don’t hold tests” (Smith-Seemiller et al., 1997).

Hold tests typically measure crystallized intelligence or stored knowledge and skill (Lezak et al., 2004). Stored knowledge and skills might include reading pronunciation (McGurn et. al, 2004) and vocabulary knowledge (Yuspeh, Vanderploeg, & Kershaw, 1998). For a hold test to be considered appropriate for estimating pre-morbid intellectual functioning, it must be assessed for validity and reliability in the neurological populations for whom the researchers create the equation, e.g., TBI or Alzheimer’s (Green et al., 2008). It is important to establish reliability and validity in the neurological populations intended because of the potential impact of under or overestimating pre-morbid functioning. It is possible for a reading test to provide an accurate estimate in a person with dementia, but it may underestimate functioning in a patient with aphasia.

Green et al. (2008) investigated the validity of the Wechsler Test of Adult Reading, a known “hold” test, because of its emphasis on reading ability and on measuring pre-morbid intellectual functioning in patients with TBI. They observed that the WTAR was a valid measure of an individual’s pre-morbid level of functioning taking several variables into account, e.g., severity, English proficiency, no prior learning disability, and no speech concerns both prior (based on report) and post-accident. Ball, Hart, Stutts, Turf, and Barth (2007) also studied the validity of the WTAR reading subtest in estimating pre-morbid functioning and found it to be the strong predictor, except for in cases where the individual has high education levels such as a doctorate.

The North American Reading Test (NART), a test measuring one's ability to read sight words and word passages, is also a hold test considered appropriate for estimating pre-morbid intellectual functioning. Studies have found that although the NART is valid, reliance on the test might underestimate levels of pre-morbid functioning and the overall effects of the brain injury (Morris et al., 2005). Researchers suggest because of the NART's general underestimation of pre-morbid functioning, it might be best used in combination with demographic variables to get a more accurate representation of pre-morbid functioning (Crawford & Allan, 1997).

Historical Test Performance

If available, tests administered prior to an injury provide valuable insight into a person's pre-morbid intellectual functioning. Reynolds (1997) proposed that historical test performance is "one of the very best means of estimating premorbid IQ or ability" (p. 775) and suggested that data obtained from standardized IQ or achievement assessment were superior to grades in determining pre-morbid intellectual functioning. This was in part due to standardized assessments being a better method to compare individuals of the same age, gender, and education level to peers, making it a more reliable estimate over grades, which tend to be subjective and not universal.

A common difficulty in using historical test performance in estimating pre-morbid intellectual functioning is the lack of previous test data for many children and adults. Many individuals, unless already identified for a learning disability or other achievement impacting disability, will not have any prior testing to provide insight on their pre-morbid functioning. Baade and Schoenberg (2004) found that prior test data were valuable but were more likely to be available for adults than for children. When possible, historical test data should be utilized in estimating pre-morbid intellectual functioning as it should provide the most objective data out of all of the estimating methods.

Familial IQ and Parent Occupation

Using the IQ of other family members to assess pre-morbid intellectual functioning is not a common practice but is still worth noting. There is some debate as to the accuracy of estimation using this method as well as the appropriateness of the method. Some researchers recommend the use of using familial IQ in estimation, cautioning that it is best when data are provided from an identical twin. Otherwise, it is no different than using demographic variables in estimating one's pre-morbid functioning (Baron, 2005; Reynolds, 1997).

Parent occupation has also been evaluated as a method of estimating a child's pre-morbid intellectual functioning. For example, Reynolds and Gutkin (1979) found that using the father's occupation in addition to demographic variables accounted for approximately 50-67% of the variance in pre-morbid intellectual functioning. This method was considered valid at the time but is not commonly used among clinicians today.

Combined Current Performance and Demographic Variables

Prior work suggests that pre-morbid intellectual functioning is best estimated using historical test data. However, as described above, previous assessment data are rarely available to estimate pre-morbid intellectual functioning. With the lack of historical data for insight on pre-morbid functioning, a combination of demographic and current assessment variables that are less sensitive to neurological insult might be the best method (Schoenberg, Scott, Duff, & Adams, 2002; Vanderploeg, 1994).

Many researchers have attempted to combine current performance and demographic variables in a regression equation to estimate pre-morbid intellectual functioning. The most popular is the Oklahoma Premorbid Intelligence Estimate-3 (OPIE-3), developed by Schoenberg and colleagues (2002). The OPIE-3 formula uses demographic variables of age, education, ethnicity, region of country, and gender along with Wechsler Adult Intelligence Scale-III (WAIS-III) subtest raw scores of matrix reasoning, picture completion, vocabulary, and information. The subtests were selected because of previous research indicating they were resistant to neurological dysfunction (Axelrod, Vanderploeg & Schinka, 1999; Donders, Tulsky, & Zhu, 2001).

Five prediction equations were developed to estimate Full Scale IQ using the previously mentioned demographic variables and subtests including an equation using only the Vocabulary (voc) subtest, Vocabulary and Matrix Reasoning (MR), and Matrix Reasoning only to estimate the Full Scale IQ. Coding variables were provided so the analysis was consistent across users. Coding variables were necessary to provide a numerical entry for a categorical variable such as gender, ethnicity, and region of country. One equation created using Vocabulary and Matrix Reasoning subtests was as follows: FSIQ = 45.997 + .652 (voc. raw score) + 1.287 (MR raw score) + .157 (age in years) + 1.034 (education) + .652 (ethnicity) – 1.015 (gender), standard error of the estimate was 6.63.

The OPIE-3 formulas (Schoenberg, Duff, Scott, Patton, & Adams, 2006) were analyzed to determine if errors in estimating varied across 13 age groups of the WAIS-III (i.e., 16-17, 18-19, 20-24, 25-29,30-34, 35-44,45-54,55-64, 65-69, 70-74, 75-79, 80-84 and 85-89 years of age). They found that the formula resulted in underestimates of predicted IQ at the extremes (individuals under 20 and individuals over 79 years of age), while overestimating pre-morbid IQ for individuals in the 35 to 54 age groups. These results indicated that while the OPIE-3formulas were a valid method of estimating pre-morbid intellectual functioning, caution should be used when interpreting the results depending on the age of the individual tested.

Schoenberg et al. (2007) used the Canadian Wechsler Intelligence Scale for Children-Fourth Edition (WISC-IV) subtests along with demographic variables to predict pre-morbid intellectual functioning in children and adolescents. Schoenberg and colleagues used the standardization sample from the WISC-IV to create regression algorithms to predict pre-morbid functioning. After splitting the group randomly, one for development and one for validation, a one-way analysis of variance (ANOVA) and Chi-Square analyses were used to examine differences between the two groups. Next, a series of hierarchical regression analyses was used to create prediction algorithms using the demographic variables of age, parent education, ethnicity, gender, and region of country along with the WISC-IV information, vocabulary, matrix reasoning, and picture completion subtests. Schoenberg et al. dummy coded all variables except age and parent education because statistically, categorical variables should not be considered continuous variables since the variables would be inappropriately weighted, thereby affecting the outcome of the analysis. It is worth noting that these equations were of the few that used dummy variables in categorical variables, making it more statistically reliable and valid.

Schoenberg and colleagues' (2007) study found the sole use of demographic variables accounted for only 22% of the variance described in the model. However, when subtest data were included with demographic variables, 45-75% of the variance was explained by the model. Twelve algorithms were created to estimate pre-morbid functioning in children using demographic data and a combination of demographic and WISC subtest data. The algorithms were similar to the ones created by Schoenberg et al. (2002) using the Wechsler Adult Intelligence Scale-Third Edition. An example of an algorithm created using the WISC-IV subtests of Vocabulary and Matrix Reasoning is as follows: FSIQ = 89.701 + 1.113 (voc raw score) + 1.181 (MR raw score) – 4.761 (age) + ethnicity + gender, standard error of the estimate = 69.3. As with the previously created equations using the WAIS-III data, coding variables were provided to allow for a more accurate estimate.

Other researchers have created equations using both current test performance and demographic variables. Vanderploeg and Schinka (1995) used regression equations to estimate pre-morbid intellectual functioning using the Wechsler Adult Intelligence Scale-Revised (WAIS-R) standardization sample data. Vanderploeg, Schinka, Baum, Tremont, and Mittenberg (1998) used current test scores along with demographic variables, which accounted for approximately 50-67% of the variance. One difference between the equations created by Vanderploeg and Schinka (1995) and other researchers was the removal of the urban/rural location and geographic region in the analyses because previous research indicated they were trivial and did not significantly contribute to the equations. At the time, their equations accounted for more variance than in other prediction equations using the WAIS or the WAIS-R. In addition, studies have shown that demographic variables of parent education level and child's ethnicity accounted for 20-28% of variance. In studies combining intelligence subtests scores and demographic variables, 50-67% of the variance was explained (Schoenberg et al., 2007).

Assumptions of Estimating Pre-morbid IQ

As with many research outcomes, assumptions must be met in order for a method of estimating pre-morbid intellectual functioning to be considered valid. Schoenberg et al. (2007) reported on the assumptions necessary for estimating pre-morbid intellectual functioning including qualifications for using the equation with healthy versus neurologically impaired individuals. In particular, when using the equations with healthy individuals, Schoenberg et al. suggested that the difference between the actual and estimated IQ score should not be significantly different. Further, they suggested that when using the equation with neurologically impaired individuals, the predictions should be greater than actual performance on IQ measures and the mean of the assumed predicted IQ scores of the clinical sample should estimate the mean of actual Full Scale IQ scores of healthy individuals (i.e., mean = 100, standard deviation = 15).

Researchers have found that assessing pre-morbid functioning in children is much more complex than estimating adult pre-morbid functioning due to the neuropsychological development of cognitive constructs that occur during childhood (Kaufman, 1990; Sattler, 1988, 2001). Many researchers cautioned clinicians with regard to interpreting pre-morbid estimates of children due to childhood cognitive development. It has also been found that using the pre-morbid equations to predict functioning 8-12 months after an injury might be an underestimate because of the changes in neurological functioning that typically occur during the first 6-12 months post-injury (Schoenberg et al., 2007). Finally, many of the methods utilized regression methods; there was a strong likelihood of regression toward the mean and a general restriction of the range for IQ scores (Stevens, 1985).

Issues with Current Methods of Estimation

Researchers have created various methods that can be used to estimate pre-morbid intellectual functioning in clinical populations such as TBI. The problem with the leading method of estimation--clinical interview--is that it is highly subjective with difficulty in reaching proficiency and might overestimate pre-morbid intellectual functioning (Kareken & Williams, 1994). In addition, it is clear that clinicians are not using appropriate variables to estimate pre-morbid intellectual functioning following a clinical interview. Most clinicians appear to ignore the two most important variables in estimating pre-morbid intellectual functioning--education and occupation levels of their clients (Romans & Caplan, 1994).

Methods such as regression equations are seen as being a more accurate form of estimation. Of the many equations used to estimate pre-morbid intellectual functioning available to clinicians, it is evident that the majority of the equations employ assessments that are inherently atheoretical. For example, the OPIE-3 formula (Schoenberg et al., 2002) utilized the outdated and atheoretical Wechsler scale to estimate pre-morbid intellectual functioning. The inherent flaw in using an atheoretical assessment was the uncertainty of the assessment measuring what it purported to measure. An atheoretical assessment relies on the subjective opinion of the creator as to the construct of intelligence, making the assessment another subjective measure to estimate pre-morbid intellectual functioning in individuals with TBI.

In contrast, theoretical assessments are supported by research and are constructed following the specific philosophy of a model of cognitive processing or intelligence. The use of an assessment that is representative of a theoretical model of functioning might potentially allow more valuable insight into the pre and post functioning of an individual who has suffered a traumatic brain injury. It might further the information obtained by allowing the clinician access to evidence-based interventions that are derived from test data. The theoretically based Das-Naglieri: Cognitive Assessment System was constructed utilizing PASS model constructs, making it an ideal assessment to use in estimating pre-morbid intellectual functioning in TBI populations.

Conclusion

The literature provided compelling evidence that not only is there a need for another method of estimating pre-morbid intellectual functioning but that the traditional methods in use are outdated and have the potential to provide inaccurate assessment data, potentially impacting the prognosis and selection of interventions for children with TBI. In addition, the literature suggested that the CAS provides a solid theoretical foundation in neurological functioning, making it an essential assessment to include in the field of estimating pre-morbid intellectual functioning. Luria’s framework and the application of the PASS model in the Cognitive Assessment System allows for the inclusion of the Planning and Attention, vital measures in determining the overall functioning of children following a TBI.

CHAPTER III

METHODOLOGY

Overview of the Study

The purpose of this study was to derive an equation(s) using the Das-Naglieri: Cognitive Assessment System (CAS) for estimating pre-morbid intellectual functioning for school-aged children who have suffered a traumatic brain injury (TBI). This would serve to augment the literature of estimating pre-morbid intellectual functioning to include an equation(s) that uses an assessment with foundations centered on a neuropsychological theory of intelligence and expand from the already created pre-morbid intellectual functioning formulas. Similar to other studies, this study also examined the relationship between assessment variables (e.g., domain and subtest scores) and demographic variables (e.g., gender, race, parent education) in estimating pre-morbid intellectual functioning in children with TBI.

This chapter begins with a description of subjects and sample characteristics, followed by a discussion of the Das-Naglieri: Cognitive Assessment System. Lastly, the hypotheses and statistical procedures used in this study are discussed.

Participants

The data for this study were collected as part of the standardization sample used to norm the Cognitive Assessment System (Naglieri & Das, 1997). A formal proposal was submitted to the Institutional Review Board (IRB) at the University of Northern

Colorado in Greeley, Colorado which was granted in accordance of their guidelines to conduct research with human participants and previously collected data (see Appendix C). A stratified random sample was used to closely represent the U.S. population according to the 1990 U.S. Census data. Data collection for the standardization of the CAS was completed between the fall of 1993 and the spring of 1996. A total of 2,200 children between the ages of 5 and 17 were tested to create the normative sample, including children from both general and special education, with an additional 872 participants tested to establish the reliability and validity of the CAS (Naglieri & Das, 1997).

The CAS standardization sample was determined by a stratified random sample plan obtained from 68 testing sites across the United States. Nine variables were used to select participants for the standardization sample including

1. Age (5 years 0 months to 17 years and 11 months)
2. Gender (Male, Female)
3. Race (Black, White, Asian, Native American, Other)
4. Hispanic Origin (Hispanic, Non-Hispanic)
5. Region (Midwest, Northeast, South, West)
6. Community Setting (Urban/Suburban, Rural)
7. Classroom Placement (Full-time Regular Education Classroom, Part-time Special Education Resource, Full-time Self Contained Special Education)
8. Educational Classification (Learning Disability, Speech/Language Impairment, Serious Emotional Disturbance, Mental Retardation, Giftedness, and Non-special Education)

9. Parental Educational Attainment Level (less than high school degree, high school graduate or equivalent, some college or technical school, four or more years of college). The parental educational attainment level was averaged if both mother and father data were available (Naglieri & Das, 1997).

Sample Characteristics

For standardization purposes of the CAS (Naglieri & Das, 1997), an equal number of males and females were tested, ranging from 200 to 300 total participants at each age. Of the sample of 2,200 participants, 76.9% of the participants classified themselves as White, 13.5% as Black, and 9.6% classified themselves as “Other.” In addition, 11.4% of the participants classified themselves as Hispanic, while the remaining 88.6% classified themselves as Non-Hispanic.

Participants were also sampled across four geographical regions and closely followed the distribution of the population established by the 1990 U.S. Census that divided the United States into four separate regions: Northeast (18.7%), Midwest (25.2%), South (33.8%), and West (22.5%). In addition, 74.8% of participants were from an urban community setting and the remaining 25.2% were from rural settings.

For the purpose of this study, the Cognitive Assessment System standardization sample was separated into three groups: development sample, validation sample, and TBI sample. The development sample consisted of 90% of the total sample and was used to create the equation(s) for the study. Ten percent from each age group (ages 5-7, 8-10, 11-13 and 14-17) of the standardization group were randomly assigned to the validation sample to validate the equation(s) upon completion. Males and females were equally represented based on their proportions in each age group. All individuals in the standardization sample who disclosed having a traumatic brain injury were also withheld from the development sample for further validation of the equation(s). A definition of validation and its methods relating to this study are discussed in the Statistical Procedures and Data Analysis sections.

Instrumentation

The Das-Naglieri Cognitive Assessment System

The Das-Naglieri Cognitive Assessment System (CAS) was used in the creation of the equation(s) to estimate pre-morbid intellectual functioning in school-aged children with a known TBI. The CAS provides four domain scores: Planning, Attention, Simultaneous, and Successive (PASS).

Each domain score was organized with a mean of 100 (*SD* = 15). A Full-Scale score comprising all four domains was also available with the same metrics. The four domain areas were formed through the contribution of 12 subtests (mean = 10; *SD* = 3). The number of subtests administered (12 total) depended on the battery given; a standard battery has the complete 12 subtests, while the basic battery has eight subtests. The cognitive processing scales and their subtests are depicted in Table 1 (Naglieri & Das, 1997).

Table 1

Cognitive Assessment System Domains and Subtests

Scales	Subtests
Planning	Matching Numbers* Planned Codes* Planned Connections
Attention	Expressive Attention* Number Detection* Receptive Attention
Simultaneous	Nonverbal Matrices* Verbal-Spatial Relations* Figure Memory
Successive	Word Series* Sentence Repetition* Speech Rate (ages 5-7) Sentence Questions (ages 8-17)

* Denotes subtests used in Basic Battery consisting of eight subtests. The Standard Battery has 12 subtests.

Psychometric Properties of the Cognitive Assessment System

Test-retest reliability was established using 215 children from the standardization sample for the Planning and Attention domains as well as the Speech Rate subtest because of the involvement of time in the determination of the scaled score. A split-half method was used to establish reliability for the Simultaneous and Successive domains. Reported internal reliabilities were high--the Full Scale reliability scores ranged from .95 to .97 for the Standard Battery and from .85 to .90 for the Basic Battery. The average reliabilities for the PASS Standard Battery (Naglieri & Das, 1997) are .88 (Planning), .88 (Attention), .93 (Simultaneous), and .93 (Successive).

Content validity for the CAS was determined by using experimental examination and task analysis so the subtests would mirror the process described in the PASS theory and its constructs. Construct validity, important in intelligence testing to developmental trends, was also measured. Criterion-related validity was established using the Wechsler Intelligence Scale for Children III (WISC-III), the Wechsler Preschool and Primary Scale of Intelligence-Revised (WPPSI-R), and the Scholastic Aptitude Test (SAT). The CAS was also determined to be a good predictor of academic performance when it was administered to 1,600 children in combination with the Woodcock Johnson Revised (WJ-R) Tests of Achievement (Naglieri & Das, 1997).

Additional studies were conducted with the CAS to determine the performance of special groups such as children with Attention Deficit/Hyperactivity Disorder (see Moonsamy, Jordaan, & Greenop, 2009) and children diagnosed with Mental Retardation including 22 children who had a documented TBI. Gutentag et al. (1998) compared TBI performance to a matched control sample's performance on the CAS. The TBI sample consisted of 14 males and 8 females, aged 9.8 to 17 years, who suffered a non-penetrating head injury with severity of injury ranging from moderate to severe. Results showed that children who had suffered from a TBI were more likely to obtain lower scores on Planning and Attention subtests than the matched control group. This further supported the data provided by the standardization sample of the CAS, which indicated that individuals with TBI did indeed perform worse than their peers specifically in the areas of Planning and Attention.

McCrea (2006) further validated the utility of the CAS with neurologically impaired individuals. This study attempted to determine the neuropsychological specificity of the CAS subtests in post-acute injury phase of patients with a brain lesion. Results indicated that overall the CAS served as a useful assessment for providing multiple baseline data in neurological functioning evaluation. This study, as well as others (i.e., Gutentag et al., 1998; Moonsamy et al., 2009) supported the validity of the Cognitive Assessment System with not only healthy individuals but individuals in clinical populations such as TBI as well.

Domain and Subtest Description

Planning scale. The Planning subtests were incorporated into the CAS to assess the child's ability to create a plan, apply the plan, and verify the effectiveness of the plan toward reaching the goal and modifying the plan if necessary.

Matching numbers. Each item in this subtest presented the examinee with eight rows of numbers with six numbers per row. Examinees must underline the two numbers that are the same in each row. The examinees repeated this task until the 150 seconds (s) were completed or until the examinee finished the task. The score for this subtest was the sum of ratios of the number of correctly underlined numbers and time (in seconds) to complete the task (rounded to whole numbers). Reliability coefficients on this subtest ranged from .67-.84 depending on the age of the individual.

Planned codes. There were two items for this particular Planning subtest. Each item had its own set of codes and was arranged in columns and rows. At the top of each page, a legend was provided to show the correspondence of the letters (A, B, C, D) to specific codes (XX, XO, OO, OX). Below the legend were eight rows with the numbers provided with a blank for each code. Examinees copied the codes to the corresponding letters in the boxes provided. Examinees between the ages of 5 years, 0 months and 7 years, 11 months were allotted a 120 s per item. Examinees between 8 years, 0 months and 17 years,11 months were allotted 60 s per item. The score for this subtest was the sum of ratios of the number of correct and time (in seconds) to complete the task (rounded to whole numbers). Reliability coefficients on this subtest ranged from .70-.92 depending on the age of the individual.

Planned connections. This subtest consisted of eight items. The first six items required the examinee to connect numbers in sequential order (1 to 2, 2 to 3, etc), while the last two items required the examinee to connect numbers and letters in sequential order (1 to A, A to 2, 2 to B, B to 3, etc.). Examinees between the ages of 5-7 were administered Items 1 through 5 and examinees aged 8 through 17 were administered Items 4-8. The score for this subtest was the sum of item times in seconds. Reliability coefficients on this subtest ranged from .66-86 depending on the age of the individual.

Attention Scale. Attention subtests “require the focus of cognitive activity, detection of a particular stimulus, and inhibition of responses to irrelevant competing stimuli” (Naglieri & Das, 1997, p. 17). The subtests involved the inspection of stimulus features and the decision of responding or not responding to competing stimuli.

Expressive attention. This subtest required different stimuli depending on the age of the examinee. Younger examinees, ages 5 to 7, were presented with a page of pictures with common animals. Examinees first identified whether the animal depicted was big or small. In the next item, the animals shown were sized appropriately (i.e., gorilla would be big, mouse would be depicted as small). In the final set, the size of the animals depicted was incongruent with its actual size (i.e., gorilla would be small, mouse would be big). The examinee would answer based on the actual size of the animal in real life. The items in the final set measured selective attention as the examinee was presented with competing stimuli and focused attention on the particular task at hand.

The older examinees, ages 8 to 17, were given a variation of the Stroop Test (Stroop, 1935) using different stimuli from the younger examinees although the task was the same. For the first item, examinees read 40 words distributed equally among the words red, blue, yellow, and green. For the second item, examinees named the 40 color rectangles (red, blue, yellow and green). For the third task, examinees said the color of the word (40 color words presented in the four colors with the word colors being incongruent with the printed color) rather than to read the word itself. The items in the final set measured selective attention for the same reason mentioned above for younger examinees. The score for this subtest was the ratio of the number of correct and time (in seconds) to complete the third task (rounded to whole numbers). Reliability coefficients for Expressive Attention ranged from .64-.93 depending on the age of the individual.

Number detection. Examinees were presented with a page with 18 rows of 10 numbers. Above the 18 rows of 10 numbers was a set of numbers specifying what the examinee should underline. There were two conditions-the first had numbers printed in regular typeface and the second set had numbers printed in outlined typeface. The score for this subtest was the ratio of number of correct identifications minus incorrectly marked numbers as a function of the time to complete subtest. For example, scores were negatively related to completion time such that holding the difference score constant, performance was better the less time taken to the complete the task. Reliability coefficients on this subtest ranged from .71-.89 depending on the age of the individual.

Receptive attention. This subtest contained two components dependent upon the examinees' age. Examinees aged 5 to 7 years underlined the pair of drawings that were similar in appearance or had the same name (e.g., two identical flowers or a rose and a lily). Examinees aged 8 to 17 underlines the letters that were either similar in appearance (e.g., b and b) or had the same name (e.g., b and B). The score for this subtest was the ratio of number of correct identifications minus incorrectly marked numbers as a function of the time to complete subtest. For example, scores were negatively related to completion time such that holding the difference score constant, performance was better the less time taken to the complete the task. Reliability coefficients on the Receptive Attention subtest ranged from .63-.90 depending on the age of the individual.

Simultaneous processing. Simultaneous processing subtests required the combination of separate constituents into a group of related parts using nonverbal and verbal abilities.

Nonverbal matrices. Examinees were presented with different geometric shapes that were unified through logical or spatial organization. Examinees deciphered the relationship and picked the best option (out of six) that corresponded to that relationship. The score was the total number of correct answers plus one point for each item not administered below the starting point. Reliability coefficients on this subtest ranged from .83-.93 depending on the age of the individual.

Verbal-spatial relations. An understanding of logical and grammatical descriptions of spatial relationships was required for this subtest. Examinees were presented with six drawings and a printed question at the bottom of each page that was read aloud to them. Examinees chose the option that best complemented the verbal description/sentence at the bottom of the page. The score ws the total number of correct answers plus one point for each item not administered below the starting point. Reliability coefficients on the Verbal-Spatial Relations subtest ranged from .70-.87 depending on the age of the individual.

Figure memory. Examinees were shown a page that presented a two- or three-dimensional geometric figure for five seconds after which the picture was removed. Examinees were then given a response book with a more complex geometric shape, with the original figure embedded, and would identify the original figure by indicating the lines (by tracing) that made up that figure. The score for this test was the number of correctly identified original figures plus one point for each item not administered below the starting point. Reliability coefficients on this subtest ranged from .81-.93 depending on the age of the individual.

Successive processing. Successive Processing subtests required the comprehension of linear organization of elements (numbers, words, etc.). All subtests required the examinee to comprehend information that was presented in a specific order and understand that meaning comes from the order.

Word series. The examinee was read a series of single-syllable/high frequency words ranging in length from two words to nine words. The examinee was then asked to repeat the series of words. The score for this subtest was total number of correctly recited series plus one point for each item not administered below the starting point. Reliability coefficients on Word Series ranged from .77-.91 depending on the age of the individual.

Sentence repetition. The examinee was asked to repeat a sentence that contained color words (e.g., “The blue is yellowing”). Color words were utilized to reduce sentence meaning and decreased the influence of simultaneous processing in this task. The score consisted of the total number of sentences repeated successfully plus one point for each item not administered below the starting point. Reliability coefficients on Sentence Repetition ranged from .77-.89 depending on the age of the individual.

Speech rate. Examinees were given a three-word series and were asked to repeat the series until told to stop. Eight different items comprised this subtest and the examinees were to repeat the series 10 times before stopping. The score was the total time required to complete each series. Reliability coefficients on this subtest ranged from .67-.87 depending on the age of the individual.

Sentence questions. This subtest was only administered to examinees eight and older. The examiner read a sentence and the examinee was then asked a question about the sentence. The question required an understanding of the serial placement of the words and sentence syntax. For example, the examiner might read “The blue is yellowing” and ask the examinee “Who is yellowing”; the correct answer would be “blue.” The total number of questions answered correctly was the subtest score plus one point for each item not administered below the starting point. Reliability coefficients on the Sentence Questions subtest ranged from .79-.88 depending on the age of the individual.

Statistical Procedures and Data Analysis

Descriptive analyses were conducted to provide the characteristics of the three samples used in the analysis. Although approximately 3,100 children were used in the standardization of the CAS, cases with missing data were not included in the analysis, leaving a total of 2,791 individual data to be analyzed in this study. The primary analyses concerned predictors of Planning, Attention, Simultaneous, Successive and Full Scale IQ.

These data were analyzed according to the research questions outlined via multiple linear regression (MLR). From the statistical standpoint that categorical variables should not be treated as continuous, all categorical variables used in the analysis were dummy coded (Tabachnick & Fidell, 2007). The research questions and proposed statistical analyses are below.

Q1 Which of the *Planning domain* subtests (Matching Numbers, Planned Codes, Planned Connections), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Planning Domain?

Q2 Which of the *Attention domain* subtests (Expressive Attention, Number Detection, Receptive Attention), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Attention Domain?

Q3 Which of the *Simultaneous domain* subtests (Nonverbal Matrices, Verbal-Spatial Relations, Figure Memory), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Simultaneous Domain?

Q4 Which of the *Successive domain* subtests (Word Series, Sentence Repetition, Sentence Questions, Speech Rate), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Successive Domain?

Q5 Which of the Cognitive Assessment System 12 *subtests*, in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Full Scale score?

Q6 Which of the Cognitive Assessment System four *domains* (Planning, Attention, Simultaneous, Successive), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Full Scale score?

Multiple linear regression (MLR) procedures were applied to the 12 subtests, the four domains, along with the demographic variables of parent education, age, gender, and race. Variables in the prediction equation(s) were entered using stepwise procedures. Once the variables had been entered into the equation(s), a check for the assumptions was completed to further validate the appropriateness of the equation(s) and the MLR analysis utilized in this study. The assumptions of linearity, independence of errors, normality of errors, and equality of variance (Tabachnick & Fidell, 2007) were examined.

The stepwise method used an atheoretical approach relying solely on statistical criteria to determine which variables should remain in the prediction equation (Tabachnick & Fidell, 2007). Unlike the methods of estimating pre-morbid intellectual functioning that utilize the theory regarding the stable subtests and domains of the Wechsler scales, there has yet to be a solid theoretical foundation to provide insight into the CAS subtest and domains that might prove best in estimating pre-morbid intellectual functioning. Thus, an atheoretical approach in multiple linear regression was utilized given the exploratory nature of this study. The CAS is comprised of four independent and inter-dependent domains, making it difficult to determine what domain(s) and subtest(s) might be the best predictors in estimating pre-morbid intellectual functioning as no other study has addressed or investigated the process of estimating pre-morbid ability with the CAS.

Although there is not sufficient research to determine which of the CAS domains and subtests should be factored into the regression equation(s), there have been a wide range of studies involving symptoms and impacts of TBI (i.e., Gutentag et al., 1998). Sufficient studies have been conducted to determine profiles of children who have sustained a traumatic brain injury, allowing for the following hypotheses for which of the PASS domains and subtests might prove best in estimating pre-morbid intellectual functioning.

It was hypothesized based on previous literature that significant deficits in attention and planning domains would be observed in TBI populations (Gutentag et al., 1998), that subtests from the Successive and Simultaneous domains would be more robust to TBI, and therefore, they would be more likely to account for more variance explained by the proposed equation(s). Specifically, Gutentag and colleagues (1998) found that scores between TBI and control participants were similar for Verbal-Spatial Relations, Figure Memory, and Word Series subtests. It was hypothesized that the three aforementioned subtests would work best (in combination with demographic variables) to predict pre-morbid intellectual functioning in children.

Q7 Using a subsample of children with TBI and the withheld 10% from each age group, will the equations prove valid in estimating pre-morbid intellectual processing?

Using the results of research questions one through six, prediction equations were formed. These equations were then validated using a non-clinical sample and a clinical sample. For this, validation confirmed the accuracy of the developed equations by utilizing a sub-sample of the CAS standardization data to test the equations using real data. The assessment and demographic data from the two validation groups (10% of the cases and the TBI sample) were individually entered into the previously created equation(s) and then analyzed to determine accuracy of predicted versus actual scores. Data for each group (i.e., control and TBI) were analyzed using paired-samples *t*-tests. For the control sample, if the derived equation(s) accurately predicted the Full Scale

Intelligence Quotient (FSIQ) as well as performance on the various domain measures, then there should not be a statistically significant difference between the scores. However, for the TBI sample, it was expected that predicted scores on each measure would be significantly greater than the actual scores. Following these analyses of the validation groups, the information derived was compared to prior research and theoretical expectations to determine how the equation(s) performed compared to other pre-morbid estimators.

It was hypothesized based on the previous literature that the data from the validation samples (TBI and 10% of the cases) would produce an accurate estimate of pre-morbid intellectual functioning and would meet the basic assumptions of estimating pre-morbid intellectual functioning as discussed in Chapter II.

CHAPTER IV

RESULTS

The primary goal of this study was to derive an equation(s) using the Das-Naglieri: Cognitive Assessment System (CAS) for estimating pre-morbid intellectual functioning for school-aged children who have suffered a traumatic brain injury (TBI). The second goal of this study was to examine the extent to which the CAS subtest and CAS domain scores predicted pre-morbid intellectual functioning using multiple linear regression methods. This chapter is divided into four sections: (a) analysis of missing data (b) group characteristics, (c) creation of the equation, and (d) summary of the findings as they related to the research questions proposed in Chapter I. Statistical analyses were conducted using SPSS Version 20.

Analysis of Missing Data

The deletion of cases of missing data in the analyses conducted for this study was briefly mentioned at the beginning of Chapter III as the method of choice. The purpose for deleting cases with missing data listwise was to provide the most accurate regression estimates possible for the Cognitive Assessment System in estimating pre-morbid intellectual functioning. A total of 281 cases (9%) from the overall CAS standardization sample were deleted in the former analyses. To determine the pattern of missing data, analyses compared the descriptive data of the missing data with that of the overall sample as well as univariate statistics to examine proportions of missing data.

Table 2 displays the descriptive statistics for the overall CAS standardization sample and the descriptive data for the cases with missing variables. The percentage of males and females between each sample were equal, as were the percentages of races represented in each group, with the exception of Whites who had 10% less representation in the missing data cases and Blacks who had 12% more cases represented in the missing data cases compared to the complete sample. Although there appeared to be more individuals between the ages of 5 and 9 with missing data compared to other age groups, the difference was also not statistically significant, $t < 1$. It should be noted that there were still a significant number of all genders, races, and age groups represented in the complete data that there should have been no foreseeable problems with running analyses using cases with only complete information.

Table 2

Descriptive Statistics of Demographic Variables by Missing Data and Complete Data Cases

	Missing (n = 281)		Complete Data (n = 2791)	
Variable	n	%	n	%
Gender				
Male	137	49	1335	48
Female	144	51	1450	52
Race				
White	191	68	2169	78
Black	67	24	345	12
Asian	2	1	13	.5
Native American	16	6	138	5
Other	5	2	126	5
Age				
5	66	23	269	10
6	31	11	393	14
7	33	12	410	15
8	29	10	287	10
9	30	11	253	9
10	19	6	271	10
11	20	7	185	7
12	16	6	122	4
13	17	6	167	6
14	7	2	162	6
15	6	2	123	.4
16	2	1	116	4
17	6	2	107	4

A string analysis was also conducted on each individual case of missing data to determine if any patterns resulted in a significant number of cases being represented for any single subtest compared to other subtests. For example, it was found that 11 cases resulted in similar missing data patterns of missing the Matching Numbers Subtest, Planning Domain Score, and Full Scale scores. The pattern with the most missing data (n = 66, 2.1%) had the following pattern: Planned Codes, Planning Domain, and Full Scale score. Results indicated that each string, or individual pattern of missing data, represented less than 3% of the overall sample (missing cases and complete cases combined). With each individual pattern of missing data resulting in a drastically small number of cases, it could be safe to determine that the pattern of missing subtest data was random.

Analyses to determine best predictors of CAS subtests and domains and the development of estimation equations were also conducted using the Expectation maximization (EM) method of imputation for missing variables. Expectation maximization was selected based on criteria discussed by Cohen, Cohen, West, and Aiken (2002), rendering it the best method of imputation for random missing data sets utilizing an atheoretical approach to analysis. Expectation maximization imputes missing variables through a two-step process: step one involves an analysis of all complete data to determine what values would be expected and the second step would run a maximum likelihood regression after the values had been imputed (Tabachnick & Fidell, 2007). Analyses did not result in significant differences in results as compared to the complete data only analyses.

Group Characteristics

A total of 2,791 participants were utilized in the following analyses after 281 individual cases (9%) were deleted due to missing data. Cohen et al. (2002) noted that in cases with over 3-5% missing data, imputation methods might skew the analyses and result in more errors. Thus, the data reflected only those cases with complete data. The remaining complete data cases from the CAS standardization sample were randomly divided into two groups. The first group was selected as the development sample, representing approximately 90% of the sample (development group, *n* = 2,492). The second group, comprising approximately 10% of the sample, was used to validate the equations (non-clinical validation group, *n* = 277). All cases with reported TBI served as a clinical validation group (TBI validation, *n* = 22).

The development group consisted of 2,492 individuals and was representative of the 1990 United States Census (Naglieri & Das, 1997) with slightly more females (*n* = 1283; 51.5%) than males (*n* = 1209; 48.5%). As displayed in Table 3, the development group consisted of 77.4% White participants, 12.4% Black, 4.7% Asian, 0.4% Native American, and 5.1% Other. Due to the age of the standardization sample, the sample was then compared to a recent U.S. census from 2010. Both the gender and the breakdown of race closely mimicked the general U.S. population as reported by the U.S. Census Data from 2010 (U.S. Census Bureau, 2011; see Table 3), further validating the utility of the CAS in recent years. Approximately 16.3% of the group had reported parents as having less than a high school degree for their education, 32.5% having a high school diploma or equivalent, 21.4% having some college experience, and 29.9% of the group reported parents having a college degree. Descriptive data and the number of participants per age group are displayed in Table 4.

Table 3

U.S. Census Data and Cognitive Assessment System Estimation Development Sample Demographic Breakdown by Percentage

Category		U.S. Census Data	CAS Development Sample
Race			
	White	77.1	77.4
	Black	12.9	12.4
	Native American	0.9	0.4
	Asian	5.0	4.7
	Other	4.1*	5.1
Gender			
	Female	50.9	51.5
	Male	49.1	48.5

*U.S. Census does not contain an "Other" Category. Data were retrieved by taking the difference of the sum of all races and subtracting from 100.

The non-clinical validation group consisted of 277 participants (118 male, 159 female). Table 2 showed that the non-clinical validation group consisted of 78.7% White participants, 13% Black, 3.2% Asian, .7% Native American, and 4.3% Other participants. It appeared that the non-clinical validation group approximated the development group, making the comparison between the two a valid representation of the population. Approximately 15.9% of the group had reported parents as having less than a high school degree for their education, 35% with a high school diploma or equivalent, 19.9% with some college experience, and 29.2% of the group reporting having a college degree. The number of participants per age group for the non-clinical validation group is also displayed in Table 4.

The final group included in the analyses was comprised of individuals with a reported traumatic brain injury. The TBI validation group consisted of 22 individuals: 14 males (63.6%) and 8 females (36.4%). As seen in Table 4, the TBI validation group consisted of 95.5% White participants (*n* = 21) and 4.5% Black participants (*n* = 1). Approximately 18.2% of the group had reported parents as having less than a high school degree for their education, 22.7% had a high school diploma or equivalent, 36.4% had some college experience, and 22.7% of the group had a college degree. Additional descriptive information including the number of participants per age group for the TBI validation group is also displayed in Table 4.

Table 4

Descriptive Statistics of Demographic Variables by Cognitive Assessment System Group

	Development (*n* = 2492)		Non-Clinical (*n* = 277)		TBI (*n* = 22)	
Variable	N	%	n	%	n	%
Gender						
Male	1209	48.5	118	42.6	14	36.4
Female	1283	51.5	159	57.4	8	63.6
Race						
White	1930	77.4	218	78.7	21	95.5
Black	308	12.4	36	13	1	4.5
Asian	11	.4	2	0.7		
Native American	126	5.1	12	4.3		
Other	117	4.7	9	3.2		
Age						
5	244	9.8	25	9		
6	350	14	43	15.5		
7	372	14.9	38	13.7		
8	257	10.3	30	10.8		
9	221	8.9	28	10.1	1	4.5
10	231	9.3	27	9.7	3	13.6
11	152	6.1	15	5.4	4	18.2
12	110	4.4	12	4.3		
13	140	5.6	14	5.1	3	13.6
14	117	4.7	18	6.5	6	27.3
15	108	4.3	11	4	1	4.5
16	97	3.9	6	2.2	3	13.6
17	93	3.7	10	3.6	1	4.5

Differences between development and non-clinical validation groups for age, parent education level, CAS subtest/domain standard scores, and Full Scale scores were evaluated using one-way analysis of variance (ANOVA) and are displayed in Table 5. Mean differences were expected between the development sample and the TBI validation sample, as well as between the non-clinical validation sample and the TBI validation sample so no analyses were conducted between those groups. Means and standard deviations of the Cognitive Assessment System for TBI validation sample are presented in Table 6. Means for both the development group as well as the non-clinical validation sample mirrored the general population with a mean standard score of 10 on all subtests (*SD* = 3) and means of 100 for the full scale score and domain (*SD* = 15). There were no statistical differences between the development and non-clinical validation group on any of the variables ($p > .05$; i.e., CAS measures, parent education level, age), indicating the appropriateness to create and validate the equation(s) using the current samples as they were comprised of similar group characteristics and mirrored the general population in CAS scores.

Table 5

Means and Standard Deviations of Cognitive Assessment System Scaled Scores: Development and Non-Clinical Validation

Variable		Development		Non-clinical Validation		1-Way ANOVA	
		M	*SD*	*M*	*SD*	*F*-Ratio	*p*
Domain	Subtest						
Planning		100.11	15.46	100.62	14.42	0.27	.60
	Matching Numbers(MN)	9.95	3.09	10.00	2.85	0.09	.76
	Planned Codes(PD)	10.09	2.99	10.01	2.79	0.18	.67
	Planned Connect(PN)	10.041	3.00	10.30	2.87	1.91	.17
Attention		100.68	14.98	99.78	15.39	0.91	.34
	Expressive Attention(EA)	10.05	3.08	10.17	2.87	0.36	.55
	Number Detection (ND)	10.14	3.01	10.01	3.05	1.67	.20
	Receptive Attention(RA)	10.07	3.03	9.90	2.99	0.83	.36
Simultaneous		101.16	14.92	100.47	15.05	0.54	.46
	Nonverbal Matrices(MT)	10.15	3.00	10.21	3.11	0.08	.77
	Verbal-Spatial Rel. (SV)	10.26	3.01	9.77	2.96	3.76	.05
	Figure Memory (FM)	10.32	3.06	10.18	3.06	0.43	.51
Successive		100.75	15.16	99.50	14.72	1.70	.19
	Word Series (WS)	10.10	3.07	9.87	2.94	1.40	.24
	Sentence Repetition(SR)	10.24	2.96	10.03	3.03	1.16	.28
	Sentence Questions(SQ)	10.23	3.09	10.02	2.93	1.13	.29
	Speech Rate (SSR)	10.11	3.04	9.99	2.82	0.35	.55
Full Scale		100.53	15.43	99.74	15.13	0.64	.42
Parent Education Level		13.46	1.91	13.40	1.91	0.19	.67
Age (in years)		9.42	3.47	9.33	3.37	0.17	.68

Table 6

Means and Standard Deviations of Cognitive Assessment System Scaled Scores: Traumatic Brain Injury

Variable		TBI	
Domain	Subtest	*M*	*SD*
Planning		80.95	17.06
	Matching Numbers(MN)	7.45	3.31
	Planned Codes(PD)	6.05	3.05
	Planned Connect(PN)	7.32	3.11
Attention		87.23	19.56
	Expressive Attention(EA)	9.09	3.13
	Number Detection (ND)	9.18	3.25
	Receptive Attention(RA)	7.27	3.99
Simultaneous		94.00	14.06
	Nonverbal Matrices(MT)	8.73	2.68
	Verbal-Spatial Rel. (SV)	7.36	3.30
	Figure Memory (FM)	9.41	2.34
Successive		91.41	11.42
	Word Series (WS)	9.27	2.201
	Sentence Repetition(SR)	8.73	2.51
	Sentence Questions(SQ)	8.77	1.88
	Speech Rate (SSR)	7.59	2.95
Full Scale		84.86	16.39
Parent Education Level		13.45	1.82
Age (in years)		13.00	2.31

Note. Domain scores (Planning, Attention, Simultaneous and Successive) are organized with a mean of 100 and a standard deviation of 15. Subtest scores are organized with a mean of 10 and a standard deviation of 3.

Research Questions

In the following sections, analyses and results for the seven research questions proposed in Chapters I and III are presented.

Q1 Which of the *Planning domain* subtests (Matching Numbers, Planned Codes, Planned Connections), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Planning Domain?

Q2 Which of the *Attention domain* subtests (Expressive Attention, Number Detection, Receptive Attention), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Attention Domain?

Q3 Which of the *Simultaneous domain* subtests (Nonverbal Matrices, Verbal-Spatial Relations, Figure Memory), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Simultaneous Domain?

Q4 Which of the *Successive domain* subtests (Word Series, Sentence Repetition, Sentence Questions, Speech Rate), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Successive Domain?

Q5 Which of the Cognitive Assessment System 12 *subtests*, in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Full Scale score?

Q6 Which of the Cognitive Assessment System four *domains* (Planning, Attention, Simultaneous, Successive), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Full Scale score?

Q7 Using a subsample of children with TBI and the withheld 10% from each age group, will the equation prove valid in estimating pre-morbid intellectual processing?

Creation of the Equation

The exploratory nature of this study and the lack of a theoretical model to drive predictor variable selection necessitated the use of stepwise regression. To determine the best CAS subtest predictor, each subtest was entered into a regression equation using the stepwise method. Stepwise regression allows the entry of variables in a regression equation based purely on statistical criteria (Tabachnick & Fidell, 2007). Cohen et al. (2002) cautioned the use of stepwise method unless a ratio of at least 1 variable per 40 cases were available (i.e., a large *n*) and a cross-validation sample was utilized to validate the results. This study had a ratio that well exceeded that suggested by Cohen et al. and a cross-validation sample was utilized to help determine the efficacy of the created equations in estimating pre-morbid intellectual functioning.

The stepwise regression method allowed all CAS-subtests to be analyzed solely for their contribution to predicting each respective domain score as well as the full scale score. The CAS-subtests that most strongly predicted the domain scaled score were selected. The same procedure was introduced to select the top CAS-domain predictor variables of full scale IQ.

Although summary results for the equations can be found in Table 31, full equations are presented in the following section as well as in Appendix A. All equations were significant predictors of Full Scale scores and Domain Scores.

Summary of Findings

To illustrate how the equation works in practice, a case from the CAS standardization sample is presented throughout the Summary of Findings. Specifically, a 14-year-old Native American male's data as presented in the CAS Standardization sample serves as an example of the equation's use in practice. His CAS assessment data are as follows:

Table 7

Cognitive Assessment System Standardization Sample Example: Native American Male

CAS Domain/Subtest		Score
	Planning	106
Matching Numbers		12
Planned Codes		9
Planned Connections		12
	Attention	121
Expressive Attention		13
Receptive Attention		12
Verbal-Spatial Relations		15
	Simultaneous	81
Nonverbal Matrices		10
Number Detection		7
Figure Memory		4
	Successive	113
Word Series		13
Sentence Repetition		12
Sentence Questions		12
Speech Rate		11
	Full Scale	107

Q1 Which of the Planning domain subtests (Matching Numbers, Planned Codes, Planned Connections) in combination with demographic variables of parent education level, race and gender are best predictors in assessing pre-morbid intellectual functioning in school aged children for the Planning Domain?

A stepwise regression method was utilized to determine which of the Planning domain subtests were best in predicting pre-morbid intellectual functioning in school aged children. This was a purely data-driven approach to determining which subtests were most useful in predicting the Planning domain, thereby predicting pre-morbid intellectual functioning. It was determined that Matching Numbers and Planned Codes were the best predictors of the Planning domain (see Table 8). These CAS-subtests were then entered into the final regression equation. Of particular interest, the two best predictor subtests were utilized in the administration of the Basic Battery of the CAS, meaning that the Extended or full version of the CAS might not need to be administered to predict pre-morbid intellectual functioning in the area of Planning.

Table 8

Stepwise Regression: Best Predictor Variables for Planning Domain

Predictor	*B*	SE	95% CI
Matching Numbers	2.99**	0.04	[2.91, 3.07]
Planned Codes	2.55**	0.04	[2.47, 2.62]
R^2	0.89		
F	10299.18**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

In view of the regression findings, the following equations are a product of entering in the two best contributors, the single best contributor, and solely demographic variables. Three equations were created using this information to estimate pre-morbid intellectual functioning for the Planning Domain.

Planning Estimate Equation 1: Top Two Cognitive Assessment System Subtests and Demographics

The first equation was created by forcing Matching Numbers and Planned Codes into the equation, followed by the demographic variables of gender, parent education level and race. Table 9 gives the formula for Planning Estimate Equation 1.

Table 9

Regression Results Summary for Estimating Planning Domain Score from Demographic Variables and Cognitive Assessment System-Subtests Standard Scores

Predictor	*B*	SE	95% CI
Constant	43.91**	0.48	[42.97, 44.85]
Matching Numbers	2.97**	0.04	[2.89, 3.05]
Planned Codes	2.53**	0.04	[2.45, 2.61]
Gender			
Male	0.34	0.20	[-0.05, 0.73]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	1.10**	0.31	[0.49, 1.71]
Some College	0.86**	0.33	[0.21, 1.51]
College Grad	2.11**	0.32	[1.48, 2.74]
Race			
White	0	0	
Black	-2.28	0.31	[-2.89, -1.67]
Asian	-0.54	0.48	[-1.48, 0.40]
Other	-0.25	0.46	[-1.15, 0.65]
Native American	2.18**	1.50	[-0.76, 5.12]
R^2	0.90		
F	2172.71**		

Note. N = 2492. CI = Confidence Interval. SE = Standard Error
* p < .05. **p < .01.

For example, a 14 year old Native American (2.180) male (.337) with a reported parent education level of college graduate (2.114) and subtest standard scores for Matching Numbers (12)(2.972) and Planned Codes = (9)(2.537) would have an estimated Planning domain score of 107 using Equation 1 (i.e., 43.914 + 2.972(12) + 2.537(9) + .337 + 2.114 + 2.180 = 107.04.)

Planning Estimate Equation 2: Top Cognitive Assessment System Subtest and Demographics

Another equation was formulated using the CAS-subtest that made the most contribution, Matching Numbers, in combination with the demographic variables listed previously. Table 10 gives the formula for Planning Estimate Equation 2 using one CAS-subtest in combination with demographic variables.

Table 10

Regression Results Summary for Estimating Planning Domain Score from Demographic Variables and Cognitive Assessment System-Subtest Standard Score

Predictor	*B*	SE	95% CI
Constant	59.21**	0.70	[57.84, 60.58]
Matching Numbers	4.07**	.06	[3.95, 4.19]
Gender			
Male	-1.79**	0.33	[-2.43, -1.14]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	1.44**	0.51	[0.44, 2.43]
Some College	1.10*	0.55	[0.02, 2.18]
College Grad	2.80**	0.52	[1.78, 3.82]
Race			
White	0	0	
Black	-3.12**	0.51	[-4.12, -2.12]
Asian	2.56	0.79	[1.01, 4.11]
Other	0.50	0.76	[-0.99, 1.99]
Native American	3.57	2.48	[-1.29, 8.44]
R^2	0.72		
F	711.12**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. **$p < .01$.

Using the same data from the previous example with the codes provided, a 14-year-old Native American (3.571) male (-1.791) with a reported parent education level of college graduate (2.799) and CAS subtest standard scores of 12 for Matching Numbers (4.073) would have an estimated Planning domain score of 112 using Equation 2 (i.e., 59.211+4.073(12)+(-1.791)+2.799+3.571= 112.6.)

Planning Estimate Equation 3:
Demographic Only

Planning Estimate Equation 3 was constructed using only demographic variables. All of demographic variables were forced into the equation, giving another option in estimating Planning Domain scores for an individual as depicted in Table 11.

Table 11

Regression Results Summary for Estimating Planning Domain Score from Demographic Variables Only

Predictor	*B*	SE	95% CI
Constant	98.24**	0.84	[96.59, 99.89]
Gender			
Male	-5.08**	0.59	[-6.24, -3.92]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	3.90**	.91	[2.13, 5.68]
Some College	4.27**	.985	[2.34, 6.20]
College Grad	7.72**	.94	[5.28, 8.96]
Race			
White	0	0	
Black	-4.18	.92	[-5.98, -2.38]
Asian	10.11**	1.41	[7.35, 12.87]
Other	1.06	1.37	[-1.63, 3.75]
Native American	-1.98	4.46	[-10.72, 6.75]
R^2	0.10		
F	33.14**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

Using the same data from the previous two examples with the codes provided, a 14-year-old Native American (-1.983) male (-5.075) with a reported parent education level of college graduate (7.717) would have an estimated Planning domain score of 98.896 using Equation 3 as follows: 98.237 + (-5.075) + 7.717 + (-1.983) = 98.896.

By using an actual case from the standardization sample of the CAS, a comparison between actual and estimated scores was easily obtained to cross-reference the two scores. The 14-year-old Native American boy was randomly selected from the non-clinical CAS standardization sample and was utilized as a reference to help showcase the validity of the equations. As is apparent in Table 12, utilizing Planning Estimate Equation 1 (top 2 contributing CAS subtests and demographic variables) would produce similar estimates to the actual Planning Domain score, indicating that it might be the most appropriate equation.

Table 12

Native American Example with Predicted and Actual Score for the Planning Domain

Equation	Predicted Score	Actual Score	Difference
Planning Est. Equation 1	107.04	106	1.4
Planning Est. Equation 2	112.66	106	6.66
Planning Est. Equation 3	98.86	106	-7.14

Q2 Which of the Attention domain subtests (Expressive Attention, Number Detection, Receptive Attention) in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Attention Domain?

Similar methods were utilized to determine the best subtests in predicting pre-morbid intellectual functioning in the Attention Domain as they were in the selection of Planning Domain subtests. A data-driven approach was utilized during which all subtests were entered in a regression equation using the stepwise method to determine which subtests contributed to the prediction of the Attention domain. It was determined that Receptive Attention and Expressive Attention were the best predictors of the Attention domain (see Table 13). These subtests were then entered into the final regression equation. Expressive Attention is a subtest that can be administered in both the Basic and Extended version of the CAS, making the application of these equations increasingly valuable in administering the assessment as the complete assessment might not need to be administered to obtain pre-morbid estimates.

Table 13

Stepwise Regression: Best Predictor Variables for Attention

Predictor	*B*	SE	95% CI
Receptive Attention	3.10**	0.04	[3.03, 3.17]
Expressive Attention	2.43**	0.04	[2.36, 2.50]
R^2	0.89		
F	10103.57**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. **$p < .01$.

The following equations are a product of entering in the two best contributors, the single best contributor, and solely demographic variables. Three equations were created using this information to estimate pre-morbid intellectual functioning for the Attention Domain.

Attention Estimate Equation 1: Top Two Cognitive Assessment System Subtests and Demographics)

The first equation was created by forcing Receptive Attention and Expressive Attention into the equation, followed by the demographic variables of gender, parent education level. and race. Table 14 gives the formula for Attention Estimate Equation 1 using two CAS-subtests in combination with demographic variables.

Table 14

Regression Results Summary for Estimating Attention Domain Score from Demographic Variables and Cognitive Assessment System-Subtests Standard Scores

Predictor	*B*	SE	95% CI
Constant	45.58**	0.49	[44.62, 46.53]
Receptive Attention	3.07**	0.04	[3.00, 3.15]
Expressive Attention	2.43**	0.04	[2.36, 2.50]
Gender			
Male	-0.55**	0.20	[-0.95, -0.15]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.09	0.31	[-0.69, 0.51]
Some College	0.11	0.33	[-0.54, 0.76]
College Grad	0.40	0.32	[-0.23, 1.02]
Race			
White	0	0	
Black	-0.533	0.310	[-1.14, 0.07]
Asian	0.02	0.48	[-0.92, 0.97]
Other	-1.278**	0.46	[-2.18, -0.37]
Native American	-0.66	1.50	[-3.60, 2.28]
R^2	0.89		
F	2034.05**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

Following the same example outlined in the Planning Estimate Equations, a 14-year-old Native American (-.660) male (-.552) with a reported parent education level of college graduate (.397) and subtest standard scores of 12 for Receptive Attention (3.074) and 13 for Expressive Attention (2.427) would have an estimated Attention domain score of 113, using Attention Estimate Equation 1: 45.577 + 3.074(12) + 2.427(13) + (-.552) + .397 + (-.660) = 113.23.

Attention Estimate Equation 2: Top Cognitive Assessment System Subtest and Demographics

Equation 2 was formulated using the subtest that made the most contribution, Receptive Attention, in combination with the demographic variables listed above. Table 15 gives the formula for Attention Estimate Equation 2--the formula that utilized one CAS-subtest in combination with demographic variables.

Table 15

Regression Results Summary for Estimating Attention Domain Score from Demographic Variables and Cognitive Assessment System-Subtest Standard Score

Predictor	*B*	SE	95% CI
Constant	60.10**	0.75	[58.63, 61.56]
Receptive Attention	3.98**	0.06	[3.87, 4.09]
Gender			
Male	-0.70*	0.35	[-1.37, -0.03]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.48	0.52	[-0.54, 1.50]
Some College	0.89	0.57	[-0.22, 2.00]
College Grad	2.27**	0.54	[1.20, 3.33]
Race			
White	0	0	
Black	-1.82**	0.53	[-62.8, -0.79]
Asian	1.29	0.82	[-0.31, 2.89]
Other	0.63	0.79	[-0.91, 2.17]
Native American	-0.78	2.55	[-5.78, 4.22]
R^2	0.69		
F	599.09**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

For example, the 14-year-old Native American (-.781) male (-.702) with a reported parent education level of college graduate (2.265) and CAS-subtest standard score of 12 for Receptive Attention (3.979) would have an estimated Attention domain score of 108 using Attention Estimate Equation 2 as follows: 60.095 + 3.979(12) + (-.702) + 2.265 +(-.781) = 108.625.

Attention Estimate Equation 3:
Demographic Only

Attention Estimate Equation 3 was constructed in which all of the demographic variables were forced into the equation, giving another option in estimating Attention Domain scores for an individual. Table 16 gives the formula for Attention Estimate Equation 3.

Table 16

Regression Results Summary for Estimating Attention Domain Score from Demographic Variables Only

Predictor	*B*	SE	95% CI
Constant	99.06**	0.81	[97.47, 100.65]
Gender			
Male	-5.36**	0.57	[-6.49, -4.24]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	3.56**	0.88	[1.84, 5.28]
Some College	4.36**	0.96	[2.48, 6.23]
College Grad	7.64**	0.91	[5.86, 9.43]
Race			
White	0	0	
Black	-3.54**	0.89	[-5.29, -1.79]
Asian	8.27**	1.37	[5.58, 10.96]
Other	1.16	1.33	[-1.45, 3.77]
Native American	0.81	4.33	[-7.67, 9.29]
R^2	0.09		
F	14.28**		

Note. N = 2492. CI = Confidence Interval. SE = Standard Error
* p < .05. **p < .01.

The 14 year old Native American (.810) male (-5.363) with a reported parent education level of college graduate (7.642) would have an estimated Attention domain score of 102 using Attention Estimate Equation 3: 99.060 + (-5.363) + 7.642 + (.810) = 102.14.

Table 17 shows the predicted scores from the Attention Estimate Equations and the actual Attention Domain scores obtained by the 14-year-old Native American that was selected from the CAS Standardization Sample. Similar to the Planning Domain Estimates, the best estimation equation in the Attention Domain was Attention Estimate

Equation 1--the equation that utilized the best two CAS-subtests in combination with demographic variables. Contrasted to the Planning domain estimate equations, it appears that the prediction equations for the Attention subtests were not as effective.

Table 17

Native American Example with Predicted and Actual Score for the Attention Domain

Equation	Predicted Score	Actual Score	Difference
Attention Est. Equation 1	113.23	121	-7.77
Attention Est. Equation 2	108.62	121	-12.38
Attention Est. Equation 3	102.14	121	-18.86

Q3 Which of the Simultaneous domain subtests (Nonverbal Matrices, Verbal-Spatial Relations, Figure Memory) in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Simultaneous Domain?

The same analyses were conducted as in the Planning and Attention domain to determine the best subtests in predicting pre-morbid intellectual functioning in school aged children. As evident from Table 18, it was determined that Figure Memory and Verbal-Spatial Relations were the best predictors of the Simultaneous domain. These subtests were then entered into the final regression equation. As with the Attention Domain, one of the subtests from the Simultaneous domain could be administered in the Basic Battery of the CAS, Verbal-Spatial Relations. This allowed some flexibility with the administration of the CAS as not all subtests would need to be administered to determine current Full Scale and Domain scores as well as predict pre-morbid functioning at the Full Scale and Domain levels.

Table 18

Stepwise Regression: Best Predictor Variables for Simultaneous

Predictor	*B*	SE	95% CI
Figure Memory	2.88**	0.04	[2.80, 2.96]
Verbal-Spatial Relations	2.55**	0.04	[2.47, 2.63]
R^2	0.87		
F	8188.39**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* *p* < .05. ***p* < .01.

The following equations are a product of entering in the two best contributors, the single best contributor, and solely demographic variables. Three equations were created using this information to estimate pre-morbid intellectual functioning for the Simultaneous Domain.

Simultaneous Estimate Equation 1: Top Two Cognitive Assessment System Subtests and Demographics

Simultaneous Estimate Equation 1 was created by forcing Figure Memory and Visual-Spatial Relations into the equation, followed by the demographic variables of gender, parent education level, and race. Table 19 gives the formula for Simultaneous Estimate Equation 1.

Table 19

Regression Results Summary for Estimating Simultaneous Domain Score from Demographic Variables and Cognitive Assessment System-Subtests Standard Scores

Predictor	*B*	SE	95% CI
Constant	45.98**	0.52	[44.93, 47.00]
Figure Memory	2.78**	0.04	[2.70, 2.86]
Verbal-Spatial Relations	2.49**	0.04	[2.41, 2.57]
Gender			
Male	-0.10	0.214	[-0.52, -0.32]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.65*	0.33	[0.004, 1.29]
Some College	1.13**	0.36	[.42, 1.83]
College Grad	2.21**	0.35	[1.52, 2.90]
Race			
White	0	0	
Black	-1.66**	0.34	[-2.32, -0.99]
Asian	1.62**	0.51	[.61, 2.62]
Other	.27	0.50	[-.71, 1.24]
Native American	-2.52	1.61	[-5.68, 0.64]
R^2	0.87		
F	1709.27**		

Note. N = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. **$p < .01$.

Following the same example outlined in the Planning Estimate Equations and the Attention Estimate Equations, a 14 year-old Native American (-2.520) male (-.100) with a reported parent education level of college graduate (2.207) and subtest standard scores of 4(2.782) and 7(2.493) would have an estimated Simultaneous domain score of 74 using Simultaneous Estimate Equation 1 as follows: 45.975 + 2.782(4) + 2.493(7) + (-.100) + 2.207 + (-2.520) = 74.14.

Simultaneous Estimate Equation 2:
Top Cognitive Assessment System
Subtest and Demographics

Simultaneous Estimate Equation 2 was created using the CAS-subtest that made the most contribution, Figure Memory, in combination with the demographic variables of gender, parent education level, and race. Table 20 gives the formula for Simultaneous Estimate Equation 2.

Table 20

Regression Results Summary for Estimating Simultaneous Domain Score from Demographic Variables and Cognitive Assessment System-Subtest Standard Scores

Predictor	*B*	SE	95% CI
Constant	60.72**	0.75	[59.25, 62.19]
Figure Memory	3.68**	0.06	[3.56, 3.79]
Gender			
Male	-0.08	0.34	[-0.76, 0.59]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	1.91**	0.53	[0.88, 2.95]
Some College	3.22**	0.58	[2.08, 4.35]
College Grad	5.56**	0.56	[4.47, 6.66]
Race			
White	0	0	
Black	-2.96**	0.54	[-4.03, -1.89]
Asian	0.39	0.83	[-1.23, 2.01]
Other	-0.52	0.80	[-2.09, 1.05]
Native American	-4.33	2.60	[-0.76, 9.42]
R^2	0.67		
F	561.49**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

The 14-year-old Native American (-4.330) male (-.082) with a reported parent education level of college graduate (5.561) and CAS-subtest standard score of 4(3.677) would have an estimated Simultaneous domain score of 76 using Simultaneous Estimate Equation 2: 60.716 + 3.667(4) + (-.082) + 5.561 + (-.4330) = 76.573.

Simultaneous Estimate Equation 3:
Demographic Only

Simultaneous Estimate Equation 3 was constructed by forcing all of the demographic variables into the equation, giving another option in estimating Simultaneous Domain scores for an individual. Table 21 shows the formula for Simultaneous Estimate Equation 3. For example, the 14-year-old Native American (.-3.439) male (-.237) with a reported parent education level of college graduate (12.577) would have an estimated Simultaneous domain score of 104 using Simultaneous Estimate Equation 3 as follows: 95.814 + (-.237) + 12.577 + (.-3.439) = 104.71.

Table 22 shows the predicted scores from the Simultaneous Estimate Equations and the actual Simultaneous Domain scores obtained by the 14-year-old Native American that was selected from the CAS Standardization Sample. Unlike the Planning Domain Estimates and the Attention Domain Estimates, the best estimation equation for the Simultaneous Domain was Simultaneous Estimate Equation 2--the equation that utilized the best CAS-subtest in combination with demographic variables. Interestingly, the demographic only equation for estimating the Simultaneous domain significantly over-estimated the intellectual functioning of the Native American male example.

Table 21

Regression Results Summary for Estimating Simultaneous Domain Score from Demographic Variables Only

Predictor	*B*	SE	95% CI
Constant	95.81**	0.77	[94.30, 97.33]
Gender			
Male	-0.24	0.55	[-1.31, 0.84]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	4.25**	0.84	[2.60, 5.90]
Some College	6.47**	0.91	[4.68, 8.26]
College Grad	12.58**	0.87	[10.87, 14.28]
Race			
White	0	0	
Black	-9.17**	0.85	[-10.84, -7.50]
Asian	5.31**	1.31	[2.74, 7.88]
Other	-2.96*	1.27	[-5.45, -0.47]
Native American	-3.44	4.13	[-4.66, 11.53]
R^2	0.17		
F	62.47**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. **$p < .01$.

Table 22

Native American Example with Predicted and Actual Score for the Simultaneous Domain

Equation	Predicted Score	Actual Score	Difference
Simultaneous Est. Equation 1	74.14	81	-6.86
Simultaneous Est. Equation 2	76.57	81	-4.43
Simultaneous Est. Equation 3	104.71	81	23.71

Q4 Which of the Successive domain subtests (Word Series, Sentence Repetition, Sentence Questions, Speech Rate) in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children for the Successive Domain?

The same stepwise regression analyses were conducted as in the previous domains to determine the best subtests in predicting pre-morbid intellectual functioning in school aged children. It was determined that Sentence Repetition and Word Series were the best predictors of the Successive domain (see Table 23). These subtests were then forced into the final regression equations that were created. As with the Planning Domain, the two best predictor subtests were utilized in the administration of the Basic Battery of the CAS, meaning that the Extended or full version of the CAS did not need to be administered to predict pre-morbid intellectual functioning in the area of Planning.

Table 23

Stepwise Regression: Best Predictor Variables for Successive

Predictor	*B*	SE	95% CI
Sentence Repetition	2.97**	0.04	[2.89, 3.05]
Word Series	2.34**	0.04	[2.26, 2.42]
R^2	0.90		
F	10562.59**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* *p* < .05. ***p* < .01.

The following equations are a product of entering in the two best CAS-subtest contributors, the single best CAS-subtest contributor, and solely demographic variables. Three equations were created using this information to estimate pre-morbid intellectual functioning for the Successive Domain.

Successive Estimate Equation 1: Top Two Cognitive Assessment System Subtests and Demographics

Successive Estimate Equation 1 was created by entering Word Series and Sentence Repetition into the equation, followed by the demographic variables of gender, parent education level, and race. Table 24 provides the formula for Successive Estimate Equation 1. Following the same example outlined in the previous domain estimates, a 14-year-old Native American (-.209) male (.048) with a reported parent education level of college graduate (1.478) and subtest standard scores of 12(2.931) and 13(2.333) would have an estimated Successive domain score of 113 using Successive Estimate Equation 1 as follows: 46.363 + 2.931(12) + 2.333(13) + (.048) + 1.478 + (-.209) = 113.18.

Table 24

Regression Results Summary for Estimating Successive Domain Score from Demographic Variables and Cognitive Assessment System-Subtests Standard Scores

Predictor	*B*	SE	95% CI
Constant	46.36**	0.46	[45.47, 47.23]
Sentence Repetition	2.93**	0.04	[2.84, 3.02]
Word Series	2.33**	0.04	[2.25, 2.41]
Gender			
Male	0.05	0.20	[-0.34, 0.43]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.52	0.30	[-0.08, 1.11]
Some College	0.56	0.33	[-0.09, 1.21]
College Grad	1.48**	0.32	[0.85, 2.11]
Race			
White	0	0	
Black	0.64*	0.31	[0.03, 1.24]
Asian	0.40	0.47	[-0.52, 1.33]
Other	-0.55	0.46	[-1.45, 0.35]
Native American	-0.21	1.48	[-3.12, 2.70]
R^2	0.90		
F	2136.94**		

Note. N = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

Successive Estimate Equation 2: Top Cognitive Assessment System Subtest and Demographics

The Successive Estimate Equation 2 was created using the CAS-subtest that made the most contribution, Sentence Repetition, in combination with the demographic variables of gender, parent education level, and race. Table 25 provides the formula for Successive Estimate Equation 2.

Table 25

Regression Results Summary for Estimating Successive Domain Score from Demographic Variables and Cognitive Assessment System-Subtest Standard Score

Predictor	*B*	SE	95% CI
Constant	54.61**	0.66	[53.31, 55.91]
Sentence Repetition	4.41**	0.05	[4.31, 4.52]
Gender			
Male	0.28	0.30	[-0.32, 0.87]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.24	0.46	[-0.67, 1.15]
Some College	0.45	0.51	[-0.55, 1.44]
College Grad	1.51**	0.49	[0.54, 2.48]
Race			
White	0	0	
Black	1.29**	0.47	[0.37, 2.22]
Asian	1.64*	0.72	[0.22, 3.05]
Other	-0.63	0.70	[-2.01, 0.75]
Native American	1.29	2.27	[-3.17, 5.74]
R^2	0.76		
F	853.77**		

Note. N = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

The 14-year-old Native American (1.287) male (.277) with a reported parent education level of college graduate (1.509) and Sentence Repetition standard score of 12(4.411) would have an estimated Successive domain score of 110 using Successive Estimate Equation 2 as follows: 54.610 + 12(4.411) + (.277) + 1.509 + 1.287 = 110.61.

Successive Estimate Equation 3:
Demographic Only

The Successive Estimate Equation 3 was constructed by forcing all of the demographic variables into the equation, giving yet another option in estimating Successive Domain scores for an individual. Table 26 displays the formula for Successive Estimate Equation 3 including the beta weights and the standard error of estimate (SEE).

Table 26

Regression Results Summary for Estimating Successive Domain Score from Demographic Variables Only

Predictor	*B*	SE	95% CI
Constant	96.20**	0.82	[94.60, 97.80]
Gender			
Male	-0.82	0.58	[-1.96, 0.31]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	3.46**	0.89	[1.72, 5.20]
Some College	6.15**	0.96	[4.26, 8.04]
College Grad	11.46**	0.92	[9.66, 13.26]
Race			
White	0	0	
Black	-4.17**	0.90	[-5.93, -2.40]
Asian	-1.32	1.38	[-4.03, 1.39]
Other	-6.06**	1.34	[-8.69, -3.43]
Native American	-1.39	4.36	[-9.94, 7.15]
R^2	0.10		
F	34.92**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

For example, the 14-year-old Native American (-1.393) male (-.823) with a reported parent education level of college graduate (11.464) would have an estimated Successive domain score of 105 using Successive Estimate Equation 3 as follows: 96.200 + (-.823) + 11.464 + (-1.393) = 105.44.

Table 27 shows the predicted scores from the Successive Estimate Equations and the actual Successive Domain scores obtained by the 14-year-old Native American that was selected from the CAS Standardization Sample. Unlike the Simultaneous Domain Estimates, but similar to the Planning Domain Estimates and the Attention Domain Estimates, the best estimation equation for the Successive Domain was Successive Estimate Equation 1--the equation that utilized the best two CAS-subtests (Word Series and Sentence Repetition) in combination with demographic variables. The second best equation appeared to be Successive Estimate Equation 2 that utilized the single best CAS-subtest in combination with demographic variables.

Table 27

Native American Example with Predicted and Actual Score for the Successive Domain

Equation	Predicted Score	Actual Score	Difference
Successive Est. Equation 1	113.18	113	.18
Successive Est. Equation 2	110.61	113	-2.39
Successive Est. Equation 3	105.44	113	-7.56

Q5 Which of the Cognitive Assessment System 12 *subtests* in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children?

Similar methods were utilized to determine which of the 12 CAS-subtests were best in predicting pre-morbid intellectual functioning, specifically for the Full Scale score as was used to determine the best subtests for each domain. A stepwise regression analyses was conducted in which all CAS-subtests were entered into the equation, resulting in those that contributed significantly to remain in the equation and those that did not contribute significantly to be excluded in the final model. This method was a purely data-driven approach to determining the best subtests in predicting Full Scale scores as there was no current theoretical basis for the analyses.

The CAS-subtests determined to be the best predictors were the same CAS-subtests that contributed significantly to each respective domain: Matching Numbers, Planned Codes, Receptive Attention, Expressive Attention, Figure Memory, Visual-Spatial Relations, Sentence Repetition, and Word Series. The following equations were a product of entering the two best contributors in each domain, the single best contributor, and solely demographic variables. Three equations were created using this information to estimate pre-morbid intellectual functioning for the Full Scale score.

Full Scale Cognitive Assessment System-Subtest Estimate Equation 1: Top Two Cognitive Assessment System Subtests and Demographics

The Full Scale CAS-Subtest Estimate Equation 1 was created by entering the best two CAS-subtest predictors from each domain into the equation, followed by the demographic variables of gender, parent education level, and race. Table 28 provides the formula for Full Scale CAS-Subtest Estimate Equation 1.

Table 28

Regression Results Summary for Estimating Full Scale Score from Demographic Variables and Cognitive Assessment System-Subtests Standard Scores

Predictor	*B*	SE	95% CI
Constant	21.58**	0.43	[20.73, 22.43]
Matching Numbers	1.09**	0.03	[1.03, 1.15]
Planned Codes	0.92**	0.03	[0.86, 0.97]
Receptive Attention	1.10**	0.03	[1.04, 1.15]
Expressive Attention	0.86**	0.03	[0.81, 0.91]
Figure Memory	0.98**	0.03	[0.93, 1.04]
Verbal-Spatial Relations	0.91**	0.03	[0.85, 0.96]
Sentence Repetition	1.05**	0.03	[0.99, 1.11]
Word Series	0.84**	0.03	[0.78, 0.89]
Gender			
Male	0.28	0.14	[-0.01, 0.56]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.40	0.22	[-0.03, 0.82]
Some College	0.37	0.24	[-0.09, 0.84]
College Grad	1.11**	0.23	[0.66, 1.57]
Race			
White	0	0	
Black	-0.78	0.22	[-1.21, -0.34]
Asian	-0.32	0.34	[-0.99, 0.35]
Other	-0.48	0.33	[-1.12, 0.36]
Native American	-0.17	1.06	[-2.24, 1.90]
R^2	0.95		
F	2907.83**		

Note. *N* = 2492. CI = Confidence Interval. SE = Standard Error
* *p* < .05. ***p* < .01.

Using the previous example, a 14-year-old Native American (-.168) male (.276) with a reported parent education level of a college graduate (1.112) and subtest standard scores of 12(Matching Numbers = 1.090), 9(Planned Codes = .915), 12(Receptive Attention = 1.096), 13(Expressive Attention = .863), 4(Figure Memory = .983), 7(Visual-Spatial Relations = .906), 12(Sentence Repetition = 1.050) and 13(Word Series = .836) would have an estimated Full Scale score of 102.23 using Full Scale CAS-Subtest Estimate Equation 1 as follows: Full Scale = 21.584 + (12)(1.090) + (9)(.915) + (12)(1.096) + (13)(.863) + (4)(.983) + (7)(.906) + (12)(1.050) + (13)(.836) + (.276) + (1.112) + (-.168) = 102.23.

Full Scale Cognitive Assessment System-Subtest Estimate Equation 2: Top Cognitive Assessment System Subtest and Demographics

Full Scale CAS-Subtest Estimate Equation 2 was created using the CAS-subtest that made the most contribution from each domain--Matching Number, Receptive Attention, Figure Memory and Sentence Repetition--in combination with the demographic variables of gender, parent education level, and race. Table 29 provides the formula for Full Scale CAS-Subtest Estimate Equation 2.

Table 29

Regression Results Summary for Estimating Full Scale Score from Demographic Variables and Cognitive Assessment System-Subtest Standard Scores

Predictor	*B*	SE	95% CI
Constant	33.73**	0.67	[32.41, 35.05]
Matching Numbers	1.62**	0.05	[1.53, 1.71]
Receptive Attention	1.59**	0.05	[1.49, 1.69]
Figure Memory	1.38**	0.05	[1.30, 1.47]
Sentence Repetition	1.92**	0.05	[1.83, 2.00]
Gender			
Male	-0.06	0.24	[-0.54, 0.42]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.51	0.37	[-0.21, 1.24]
Some College	0.70	0.40	[-0.09, 1.49]
College Grad	1.96**	0.40	[1.18, 2.73]
Race			
White	0	0	
Black	-1.13**	0.38	[-1.87, -0.39]
Asian	0.83	0.58	[-0.313, 1.96]
Other	0.57	0.56	[-0.52, 1.66]
Native American	0.47	1.80	[-3.06, 3.99]
R^2	0.85		
F	1196.27**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. **$p < .01$.

The 14-year-old Native American (.467) male (-.061) with a reported parent education level of a college graduate (1.958) and subtest standard scores of 12(Matching Numbers = 1.620), 12(Receptive Attention = 1.589), 4(Figure Memory = 1.384), 12(Sentence Repetition = 1.916) would have an estimated Full Scale score of 103 using Full Scale CAS-Subtest Estimate Equation 2 as follows: Full Scale = 33.727 +

(12)(1.620) + (12)(1.589) + (4)(1.384) + (12)(1.916) + (-.061) + (1.958) + (.467) = 103.13.

Full Scale Demographic Estimate
Equation 1: Demographic Only

The Full Scale Demographic Estimate Equation 1 was constructed by forcing all of the demographic variables into the equation, providing a demographic only equation to estimate Full Scale pre-morbid functioning. Table 30 illustrates the formula for Full Scale Demographic Estimate Equation 1.

Table 30

Regression Results Summary for Estimating Full Scale Score from Demographic Variables Only

Predictor	*B*	SE	95% CI
Constant	96.06**	0.80	[95.90, 96.22]
Gender			
Male	-3.77**	0.57	[-4.79, -2.56]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	5.00**	0.87	[3.29, 6.71]
Some College	7.05**	0.95	[5.19, 8.91]
College Grad	13.03**	0.90	[11.26, 14.80]
Race			
White	0	0	
Black	-6.95**	0.88	[-8.67, -5.22]
Asian	7.18**	1.36	[4.51, 9.85]
Other	-2.27	1.32	[-4.86, 0.31]
Native American	-1.93	4.29	[-10.34, 6.47]
R^2	0.16		
F	59.51**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

For example, the 14-year-old Native American (-1.934) male (-3.765) with a reported parent education level of college graduate (13.028) would have an estimated Full Scale score of 103 using the Full Scale Demographic Estimate Equation 1 as follows: 96.060+ (-3.765)+13.028+(-1.934) = 103.41.

Q6 Which of the Cognitive Assessment System four *domains* (Planning, Attention, Simultaneous, Successive), in combination with demographic variables of parent education level, race and gender, are the best predictors in assessing pre-morbid intellectual functioning in school aged children?

A stepwise regression analysis was conducted wherein all four domains were entered into the regression, resulting in those that contributed significantly to remain in the equation and those that did not contribute significantly to not be included in the final model. This method was a purely data-driven approach to determining the best domains in predicting Full Scale scores as there was no theory at this point to drive the analyses. The domains were then forced into the equation along with demographic variables of gender, parent education level, and race. All variables were once again dummy-coded so as not to obfuscate the impact of the categorical variables examined.

The domains determined to be the best predictors were the Planning and Successive Domains, followed by Simultaneous and Attention (see Table 31). The following equations are a product of entering in the two best CAS-Domain contributors and the single best CAS-Domain contributor in combination with demographic variables. Two equations were created using this information to estimate pre-morbid intellectual functioning for the Full Scale score.

Table 31

Stepwise Regression: Best Cognitive Assessment System-Domain Predictor Variables for Full Scale

Predictor	*B*	SE	95% CI
Planning	0.62	0.01	[0.61, 0.64]
Successive	0.51	0.01	[0.49, 0.52]
R^2	0.86		
F	7818.78**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

Full Scale Cognitive Assessment System-Domain Estimate Equation 1: Top Two Cognitive Assessment System Domains and Demographics

Full Scale CAS-Domain Estimate Equation 1 was created by forcing Planning and Successive domains into the equation, followed by the demographic variables of gender, parent education level, and race. Table 32 provides the formula for Full Scale CAS-Domain Estimate Equation 1.

Table 32

Regression Results Summary for Estimating Full Scale Score from Demographic Variables and Cognitive Assessment System-Domains Standard Scores

Predictor	*B*	SE	95% CI
Constant	10.37**	0.97	[8.47, 12.27]
Planning Domain	0.61**	0.01	[0.59, 0.62]
Successive Domain	0.49**	0.01	[0.47, 0.50]
Gender			
Male	-0.28	0.23	[-0.72, 0.17]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	0.95**	0.34	[0.27, 1.62]
Some College	1.47**	0.38	[0.73, 2.21]
College Grad	2.77**	0.37	[2.05, 3.49]
Race			
White	0	0	
Black	-2.38**	0.35	[-3.07, -1.70]
Asian	1.67**	0.54	[0.61, 2.73]
Other	0.03	0.52	[-0.99, 1.05]
Native American	-0.05	1.68	[-3.35, 3.25]
R^2	0.87		
F	1669.20**		

Note. $N = 2492$. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

Utilizing the example used previously, a 14-year-old Native American (-.052) male (-.279) with a reported parent education level of a college graduate (2.766) and domain standard scores of 106 (Planning) and 113 (Successive) would have an estimated Full Scale score of 111 using Full Scale CAS-Domain Estimate Equation 1 as follows:

Full Scale = -10.371 + (106)(.608) + (113)(.486) + (-.279) + (2.766) + (-.052) = 111.43.

Full Scale Cognitive Assessment System-Domain Estimate Equation 2: Top Cognitive Assessment System Domain and Demographics

The Full Scale CAS-Domain Estimate Equation 2 was generated by forcing the top CAS-Domain contributor, Planning, into the equation along with the demographic variables of gender, parent education level, and race. Table 33 gives the formula for Full Scale CAS-Domain Estimate Equation 2.

Table 33

Regression Results Summary for Estimating Full Scale Score from Demographic Variables and Cognitive Assessment System-Domain Standard Score

Predictor	*B*	SE	95% CI
Constant	21.22**	1.26	[18.75, 23.68]
Planning Domain	0.76**	0.01	[0.74, 0.79]
Gender			
Male	0.10	0.35	[-0.59, 0.79]
Female	0	0	
Parents Education Level			
> HS	0	0	
HS	2.03**	0.53	[0.98, 3.07]
Some College	3.80**	0.58	[2.66, 4.94]
College Grad	7.15**	0.56	[6.05, 8.24]
Race			
White	0	0	
Black	-3.76**	0.54	[-4.82, -2.70]
Asian	-0.53	0.84	[-2.17, 1.12]
Other	-3.08**	0.81	[-4.66, -1.50]
Native American	-0.42	2.62	[-5.55, 4.71]
R^2	0.69		
F	606.56**		

Note. N = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. ** $p < .01$.

The 14-year-old Native American (-.423) male (.103) with a reported parent education level of a college graduate (7.146) and domain standard scores of 106 (Planning) would have an estimated Full Scale score of 108 using Full Scale CAS-Domain Estimate Equation 2 as follows: Full Scale = 21.218 + (106)(.762) + (.103) + (7.146) + (-.423) = 108.81.

Table 34 shows the predicted scores from all the Full Scale Estimate Equations (CAS-subtests, CAS-Domains and demographic only) and the actual Full Scale scores obtained by the 14-year-old Native American that was selected from the CAS Standardization Sample. Using the selected participant, it appears that the Full Scale CAS-Domain Equation 2 performed best in estimating pre-morbid intellectual functioning as it was closest to the actual score. This equation utilized the best CAS-Domain predictor, Planning, to estimate pre-morbid intellectual functioning in combination with the demographic variables of gender, parent education level, and race. All subtests appeared to do a sufficient job in having the estimated pre-morbid intellectual functioning mirror the actual score obtained. This was a good indicator that the equations were effective as the estimates should not differ drastically from the actual score on a non-clinical case such as the one utilized as an example throughout this chapter.

Table 34

Native American Example with Predicted and Actual Score for the Full Scale

Equation	Predicted Score	Actual Score	Difference
Full Scale CAS-Subtest Eq. 1	102.23	107	-4.77
Full Scale CAS-Subtest Eq. 2	103.13	107	-3.87
Full Scale Demographic Eq. 1	103.41	107	-3.59
Full Scale CAS-Domain Eq. 1	111.43	107	4.43
Full Scale CAS-Domain Eq. 2	108.81	107	1.81

It was determined that the Planning and Successive domains were most predictive in estimating the Full Scale IQ ($p < .05$), while the following CAS subtests were the top two contributors in estimating their respective domains ($p < .05$): (a) Matching Numbers (MN) and Planned Codes (PD) for the Planning domain, (b) Receptive Attention (RA) and Expressive Attention (EA) for the Attention domain, (c) Figure Memory (FM) and Visual-Spatial Relations (SV) for Simultaneous, and (d) Sentence Repetition (SR) and Word Series (WS) for the Successive domain. In addition, each domain was a significant predictor in estimating the Full Scale scores. Stepwise analyses and results are depicted in Table 35.

Table 35

Stepwise Regression Analyses for the Domain and Full Scale Scores

Criterion	Predictor	*B*	SE	95% CI
Full Scale Score	Planning	0.63**	0.01	[0.61, 0.65]
	Successive	0.51**	0.01	[0.49, 0.53]
	R^2	0.86		
	F	7818.78**		
Planning	Matching Numbers	2.99**	0.04	[2.92, 3.07]
	Planned Codes	2.55**	0.04	[2.47, 2.63]
	R^2	0.89	0.35	
	F	10299.18**		
Attention	Receptive Attention	3.10**	0.04	[3.02, 3.17]
	Expressive Attention	2.43**	0.04	[2.36, 2.50]
	R^2	0.89	0.35	
	F	10103.57**		
Simultaneous	Figure Memory	2.88**	0.04	[2.80, 2.96]
	Visual-Spatial Rel.	2.55**	0.04	[2.47, 2.63]
	R^2	0.87	0.35	
	F	8188.39**		
Successive	Sentence Repetition	2.97**	0.04	[2.89, 3.05]
	Word Series	2.34**	0.04	[2.26, 2.42]
	R^2	0.90		
	F	10562.59**		

Note. N = 2492. CI = Confidence Interval. SE = Standard Error
* $p < .05$. **$p < .01$.

Those variables that comprised the best predictors were then utilized to create the regression equations for this study. Sequential regression methods were utilized for the creation of the equations after stepwise regression had determined the significant contributors for each domain and full scale analysis. Sequential regression differs from stepwise regression in that it allows theoretical considerations, such as the order of entry of assessment scores versus demographic variables, to help determine when variables enter the equation (Tabachnick & Fidell, 2007). Sequential regression allowed flexibility to enter in the subtest/domain scores into the equation first before entering the demographic variables as is common practice in the estimation literature (e.g., Schoenberg et al., 2004, 2007).

For the Full Scale score, the following equations were used: (a) demographic variables only, (b) subtest standard scores and demographic variables, and (c) domain standard scores and demographic variables. In addition, prediction equations for individual domain scores were created using (a) demographic variables only, (b) subtest standard scores and demographic variables. A total of 17 equations were created to predict pre-morbid intellectual functioning at the Domain score and Full Scale IQ levels. Five regression equations incorporated only the demographic variables of gender, parent education level, and race--one for each domain and Full Scale score. Five equations were generated incorporating the two subtests that provided the most predictive value (e.g., Matching Numbers and Planned Codes), in combination with demographic variables (i.e., gender, parent education level and race), to predict each domain and Full Scale score. Five equations were generated incorporating the single best subtest predictor in combination with demographic variables in estimating domain and full scale scores.

Finally, two equations were created to predict the Full Scale score using the best domain in predicting the full scale score in combination with demographic variables and using the top two domain predictors in combination with demographic variables.

So as not to influence the contribution of the categorical variables based on arbitrarily assigned numbers, variables for gender, parent education level, and race were each dummy coded (see Schoenberg et al., 2007, for a similar approach). In the creation of the demographic only equations, all demographic variables were entered into the equation. For subsequent models (both subtest and domain), each top predicting subtest or domain variable was entered first into the equation, followed by each of the demographic variables. Regression equations and their resultant R^2, standard errors of measurement, and unstandardized beta coefficients were then developed.

Table 36

Regression Results Summary for Estimating Full Scale and Domain Scores From Demographic Variables and Cognitive Assessment System Subtest/Domain Standard Scores

Regression Model	R^2	SEE	F
Full Scale Score			
Full Scale Demographic Estimate Eq. 1	0.16	14.16	59.51**
Full Scale CAS-Subtest Estimate Eq. 1	0.95	3.48	2907.83**
Full Scale CAS-Subtest Estimate Eq. 2	0.86	5.94	1196.27**
Full Scale CAS-Domain Estimate Eq. 1	0.87	5.56	1669.20**
Full Scale CAS-Domain Estimate Eq. 2	0.69	8.64	606.56**
Planning			
Planning Estimate Equation 1	0.90	4.96	2172.71**
Planning Estimate Equation 2	0.72	8.82	711.12**
Planning Estimate Equation 3	0.10	14.72	33.134**
Attention			
Attention Estimate Equation 1	0.89	4.95	2034.05**
Attention Estimate Equation 2	0.69	8.43	599.10**
Attention Estimate Equation 3	0.09	14.28	32.17**
Simultaneous			
Simultaneous Estimate Equation 1	0.87	5.32	1709.28**
Simultaneous Estimate Equation 2	0.67	8.58	561.49**
Simultaneous Estimate Equation 3	0.17	13.63	62.47**
Successive			
Successive Estimate Equation 1	0.90	4.90	2136.94**
Successive Estimate Equation 2	0.76	7.50	853.77**
Successive Estimate Equation 3	0.10	14.39	34.92**

NOTE: N = 2492. ** $p < .001$. CAS = Cognitive Assessment System; SEE = standard error of estimate; Full Scale Demographics Estimate Eq. 1= demographic only equation; Full Scale CAS-Subtest Estimate Eq. 1 = equation utilizing Matching Numbers, Planned Codes, Receptive Attention, Expressive Attention, Figure Memory, Visual-Spatial Relations, Sentence Repetition and Word Series subtest standard scores + demographic variables to predict Full Scale IQ; Full Scale CAS-Subtest Estimate Eq. 2 = equation utilizing Matching Numbers, Receptive Attention, Figure Memory and Sentence Repetition standard scores + demographic variables to predict Full Scale IQ; Full Scale CAS-Domain Estimate Eq. 1 = equation utilizing Planning and Successive domain standard scores and demographic variable to predict Full Scale IQ s; Full Scale CAS-Domain Estimate Eq. 2 = equation utilizing Planning Domain standard scores and demographic variables to predict Full Scale IQ; Planning Estimate Equation 1 = equation utilizing Matching Numbers and Planned Codes standard scores + demographic variables to predict Planning Domain score; Planning Estimate Equation 2 = equation utilizing Matching Numbers standard score + demographic variables to predict Planning Domain score; Planning Estimate Equation 3 = demographic only; Attention Estimate Equation 1 = equation utilizing Expressive Attention and Receptive Attention subtest standard scores + demographic variables to predict Attention Domain score; Attention Estimate Equation 2 = equation utilizing Receptive Attention subtest standard scores + demographic variables to predict Attention Domain score; Attention Estimate Equation 3 = demographic only to estimate Attention; Simultaneous Estimate Equation 1 = equation utilizing Figure Memory and Visual-Spatial Relations subtest standard scores + demographics to predict Simultaneous Domain score; Simultaneous Estimate Equation 2 = equation utilizing Figure Memory subtest standard score + demographics to predict Simultaneous Domain score; Simultaneous Estimate Equation 3 = demographic only to estimate Simultaneous domain score; Successive Estimate Equation 1 = equation utilizing Sentence Repetition and Word Series subtest standard score + demographics to predict Successive Domain score; Successive Estimate Equation 2 = equation utilizing Sentence Repetition subtest standard score + demographics to predict Successive Domain score; Successive Estimate Equation 3 = demographic only to predict Successive Domain score.

The demographic information accounted for approximately 16% of the variance for the Full Scale equation while accounting for 9.4% to 16.8% of the variance on the domain equations. In addition, the equations comprising both two best CAS predictors and demographic variables accounted for 87.3 to 94.9% of the variance. Equations that combined demographic variables and the best CAS predictor accounted for 67%-75% of the overall variance in the model. It should be noted that all subtests entered into the equation (with the exception of the Receptive Attention-RA and Visual-Spatial Relations-SV) were all subtests that could be administered using the Basic Battery in addition to the extended battery. This could extend the utility of the equations by not requiring examiners to administer the full battery but rather the basic battery with the addition of two subtests--Receptive Attention and Visual-Spatial Relations.

Validation of Equations

Q7 Using a subsample of children with TBI and the withheld 10% from each age group, will the model prove valid in estimating pre-morbid intellectual processing?

To evaluate the accuracy of the equations, 17 equations were cross-validated with the non-clinical validation sample as well as the TBI validation sample. Validation once again confirmed the accuracy of the developed equations by utilizing a sub-sample of the CAS standardization data to test the equations using real data. The assessment and demographic data from the two validation groups (10% of the cases and the TBI sample) were individually entered into the previously created equation(s) and then analyzed to determine accuracy of predicted versus actual scores. Data for each group (i.e., control and TBI) were analyzed using paired-samples *t*-tests. For the control sample, if the derived equation(s) accurately predicted FSIQ as well as performance on the various domain measures, then there should not be a statistically significant difference between the scores. However, for the TBI sample, it was expected that predicted scores on each measure would be significantly greater than the actual scores. Following these analyses of the validation groups, the information derived was compared to prior research and theoretical expectations to determine how the equation(s) performed compared to other pre-morbid estimators.

This was first done by entering each of the 277 non-clinical samples and the 22 TBI sample data into each of the 17 equations. A total of five predicted Full Scale scores were estimated along with three predicted CAS-domain scores for each domain (12 in total). Descriptive statistics and paired sample t-tests are depicted in Table 37.

Table 37

Descriptive Statistics, Mean Comparisons and Significance Results Between Actual and Predicted Values for Domain and Full Scale Cognitive Assessment System Results

	Non-Clinical Validation Sample						
Actual IQ	Mean	SD	Min	Max	*p*	df	t
Full Scale	99.747	15	56	143			
Planning	100.62	14	61	139			
Attention	99.779	14	63	150			
Simultaneous	100.47	15	62	142			
Successive	99.501	14	59	139			
Predicted IQ							
Full Scale Demographic Est. Eq. 1	100.10	6.17	85	116	0.654	276	-0.448
Full Scale CAS-Subtest Est. Eq. 1	99.69	14.92	57	139	0.812	276	0.238
Full Scale CAS-Subtest Est. Eq. 2	99.74	14.07	56	135	0.994	276	0.007
Full Scale CAS-Domain Est. Eq. 1	100.18	14.07	57	134	0.184	276	-1.33
Full Scale CAS-Domain Est. Eq. 2	100.65	12.44	69	134	0.062	276	-1.871
Planning Est. Equation 1	100.10	13.39	69	144	0.059	276	1.899
Planning Est. Equation 2	100.19	12.14	70	133	0.37	276	0.898
Planning Est. Equation 3	99.61	4.51	88	116	0.213	276	1.248
Attention Est. Equation 1	**100.4**	**13.81**	61	150	**0.04**	**276**	**-2.065**
Attention Est. Equation 2	99.88	12.06	71	137	0.817	276	-0.232
Attention Est. Equation 3	100.19	4.36	90	114	0.614	276	-0.505
Simultaneous Est. Equation 1	100.13	13.66	68	135	0.296	276	1.048
Simultaneous Est. Equation 2	100.62	12.4	71	132	0.785	276	-0.274
Simultaneous Est. Equation 3	100.95	6.24	86	113	0.55	276	-0.598
Successive Est. Equation 1	99.61	14.34	62	137	0.674	276	-0.42
Successive Est. Equation 2	99.33	13.51	60	131	0.697	276	0.389
Successive Est. Equation 3	100.65	4.92	89	107	0.159	276	-1.411

*NOTE: Bold lines indicate predicted scores that are significantly different than the actual score.

Non-Clinical Validation Sample

For the non-clinical validation sample, the average predicted score across all age levels (domain and full scale) did not significantly differ on all equations except for the equation utilizing the top two Attention CAS-subtests to predict the Attention domain score (Attention Estimate Equation 2, $t(276) = -2.065$, $p=.04$); meaning that all equations were effective in estimating pre-morbid intellectual functioning in the non-clinical sample by having predicted scores that did not differ significantly from the actual scores. In addition, correlations between actual scores and predicted scores were found to be significant ($p=.000$, r ranged from .328 to .975). Table 36 shows the equation, minimum and maximum values, and the relative t value and p values.

To further analyze the accuracy of the predicted scores, a paired sample *t*-test was conducted for each individual age group to determine which equations were most appropriate depending on the age of the individual. All predicted scores did not differ from the actual score for each age group except for the age/equation combination displayed in Table 38. Although some equations resulted in significantly different predicted values than actual values, it appeared that each age group had at least one equation from each of the CAS-Domain and Full Scale categories that could be utilized to predict domain and full scale scores. Further investigation is necessary, potentially with a larger sample size, to determine the validity of the equations in Table 38 in combination with the age groups in question.

Table 38

Analyses of Cognitive Assessment System Pre-morbid Equation Accuracy by Age

Regression Model	Age	*df*	Actual (Mean)	Predicted (Mean)	*t*	*p*
Full Scale CAS-Subtest Est. Eq. 1	12	11	86	88	2.882	.015
Full Scale CAS-Subtest Est. Eq. 2	12	11	86	89	3.857	.003
Full Scale CAS-Domain Est. Eq. 1	6	42	103	101	-2.182	.035
Full Scale CAS-Domain Est. Eq. 2	12	11	86	93	2.612	.024
Planning Est. Equation 1	12	11	93	95	-2.695	.021
Planning Est. Equation 2	12	11	93	97	-2.88	.015
Planning Est. Equation 3	14	17	106	101	2.294	.035
Attention Est. Equation 1	7	37	96	98	-2.196	.034
Simultaneous Est. Equation 1	5	24	105	102	2.521	.019
Simultaneous Est. Equation 2	12	11	87	94	-2.627	.005
	16	5	86	94	-5.581	.002
Simultaneous Est. Equation 3	12	11	87	98	-2.627	.024
	13	13	108	101	2.433	.03
	16	5	86	98	-3.405	.019
Successive Est. Equation 1	14	17	106	104	2.117	.044
Successive Est. Equation 2	14	17	106	102	2.793	.012

An additional analysis common in the pre-morbid intellectual functioning literature was to determine if the estimated score differed significantly from the actual score on a number of criteria (e.g., Schoenberg et al., 2007). This study conducted additional analyses on the non-clinical validation sample to determine the differences between predicted and actual standard scores on the following criteria: (a) ±5 points, (b) ±10 points, and (c) same category. Analyses were comparable to those reported in other studies assessing pre-morbid intellectual functioning equations (i.e., Schoenberg et al., 2007). The analyses are displayed in Table 39.

Table 39

Predictive Accuracy of Estimations of Full Scale and Domain Scores: Non-clinical Validation Sample

	Percentage Within		
Equation	±5	±10	Same Category
Full Scale Demographic Est. Eq. 1	25.3	53.1	42.2
Full Scale CAS-Subtest Est. Eq. 1	87	99.6	85.2
Full Scale CAS-Subtest Est. Eq. 2	65	94.2	71.1
Full Scale CAS-Domain Est. Eq. 1	65.7	93.5	66.4
Full Scale CAS-Domain Est. Eq. 2	50.2	81.2	59.2
Planning Est. Equation 1	75.5	97.1	75.8
Planning Est. Equation 2	50.2	79.8	57
Planning Est. Equation 3	25.6	50.2	46.6
Attention Est. Equation 1	77.6	95.7	31
Attention Est. Equation 2	48.7	85.2	35
Attention Est. Equation 3	30	54.9	52.3
Simultaneous Est. Equation 1	62.1	93.1	69.3
Simultaneous Est. Equation 2	39.7	70.8	49.5
Simultaneous Est. Equation 3	28.5	52.3	40.1
Successive Est. Equation 1	73.3	96.8	72.6
Successive Est. Equation 2	50.5	81.6	63.5
Successive Est. Equation 3	29.2	55.6	53.4

Traumatic Brain Injury Validation Group

Analyzing the TBI validation group required a different interpretation than the non-clinical validation group. As mentioned in Chapter II, when predicting pre-morbid intellectual functioning in clinical samples, significant differences might indicate that the TBI group was meeting the basic assumptions of mirroring the normal population (i.e., $M = 100$; $SD = 15$). In addition, significant difference between predicted and actual scores was consistent with these predictions. The TBI validation group average predicted score across all age levels (domain and full scale) differed significantly on all but 10 equations. Table 40 shows the equation, minimum and maximum values, and the relative *t* value and *p* values. The bolded lines indicate predicted scores that were significantly different than the actual score.

Table 40

Descriptive Statistics, Mean Comparisons, and Significance Results Between Actual and Predicted Values for Domain and Full Scale Cognitive Assessment System Results for Traumatic Brain Injury Validation Sample

	TBI Validation Sample						
Actual IQ	Mean	SD	Min	Max	*p*	df	t
Full Scale	84.86	16.39	50	116			
Planning	80.95	17.05	49	106			
Attention	87.22	19.55	51	134			
Simultaneous	94	14.06	62	120			
Successive	93.40	11.41	62	110			
Predicted IQ							
Full Scale Demographic Est. Eq. 1	**100.03**	**5.64**	**85**	**109**	**.00**	**21**	**-4.773**
Full Scale CAS-Subtest Est. Eq. 1	86.16	16.36	53	120	.063	21	-1.966
Full Scale CAS-Subtest Est. Eq. 2	87.82	15.89	58	119	.025	21	-2.423
Full Scale CAS-Domain Est. Eq. 1	85.33	13.67	61	105	.697	21	-.395
Full Scale CAS-Domain Est. Eq. 2	86.02	14.16	58	108	.448	21	-.773
Planning Est. Equation 1	82.56	15.87	55	100	.08	21	-1.839
Planning Est. Equation 2	**89.65**	**14.07**	**65**	**113**	**0**	**21**	**-4.714**
Planning Est. Equation 3	**99.10**	**4.14**	**88**	**105**	**0**	**21**	**5.226**
Attention Est. Equation 1	**88.77**	**18.42**	**57**	**135**	**.003**	**21**	**-.984**
Attention Est. Equation 2	89.20	16.2	63	124	.2	21	-1.322
Attention Est. Equation 3	**99.61**	**4.18**	**90**	**106**	**.005**	**21**	**-3.15**
Simultaneous Est. Equation 1	95.96	13.91	66	120	.116	21	-1.639
Simultaneous Est. Equation 2	97.99	9.87	75	113	.022	21	-2.464
Simultaneous Est. Equation 3	**101.42**	**5.23**	**86**	**108**	**.016**	**21**	**-2.624**
Successive Est. Equation 1	94.29	10.73	68	109	.126	21	-1.594
Successive Est. Equation 2	93.379	11.16	59	107	.982	21	.023
Successive Est. Equation 3	**101.11**	**4.37**	**91**	**107**	**.003**	**21**	**-3.348**

*NOTE: Bold lines indicate predicted scores that are significantly different than the actual score.

The alpha level for all planned comparisons for each set of equations (e.g., those for the full scale estimate, planning estimates, etc.) was corrected by employing the Bonnferoni correction, whereby the alpha level (.05) was divided by the number of tests conducted. Thus, using this correction for the full scale estimates (adjusted alpha = .010) there was a reliable difference between the predicted and actual values only for the full-scale demographic estimate for Equation 1. Using this correction for the domain estimates (adjusted alpha = .016), Planning Estimate Equation 1(2 CAS-subtests) did not produce significantly different results as expected for individuals with a TBI. Attention equations 1 and 3 produced statistically different scores in the TBI validation sample, providing some evidence of its effectiveness in estimating pre-morbid intellectual functioning in clinical populations. All but one equation resulted in non-significant differences; Simultaneous Estimate Equation 3(demographic only) appeared effective in estimating pre-morbid intellectual functioning in the TBI sample by producing marginally significant different estimated scores versus predicted scores (p = .016). Two equations, Successive Estimate Equation 1 and 2, appeared less effective in estimating pre-morbid intellectual functioning in the TBI sample as evidenced by not producing significantly different estimated scores versus predicted scores as compared to Successive Estimate Equation 3 (p = .003). More validation is necessary before conclusive results can be obtained with regard to equation validity in clinical populations.

Due to the small sample size of the TBI validation sample, age related analyses per equation were not conducted. Further investigation is necessary with a large diverse sample to determine the validity of all CAS pre-morbid estimation equations on clinical samples.

CHAPTER V

DISCUSSION

This chapter reviews the purpose of the present study and summarizes the major findings while offering theoretical and practical implications of the results. Potential limitations of the current study are then discussed. Finally, suggestions for future directions are presented.

Purpose of Study

The last couple of decades have witnessed increased research seeking to estimate pre-morbid intellectual functioning of people with traumatic brain injuries (TBI) into the research discipline of traumatic brain injuries (see Schoenberg et al., 2004, 2007, 2008). Many studies have shown the deleterious effects children with TBI might face in educational settings including difficulties sustaining attention and concentration and other executive functioning deficits that affect academic performance (Semrud-Clikeman, 2001). Schools and clinics are faced with an increasing demand to provide accommodations and interventions for children with a TBI diagnosis; the ability to estimate pre-morbid intellectual functioning is essential in the determination of services as interventions will be tools designed to assist an individual in reaching their pre-injury functions, abilities, and skills.

Studies incorporating current assessment tools have historically used the Wechsler scales as their primary assessment (Schoenberg et. al, 2004, 2007; Vanderploeg et al., 1996). Including the atheoretical Wechsler scales in estimating pre-morbid intellectual functioning, despite its popularity in the practice of IQ assessment, is insufficient in view of modern theoretical, neuropsychological-based perspectives of cognitive functioning that are better connected to remedial efforts and positive outcomes, such as the Das-Naglieri Cognitive Assessment System (Naglieri & Das, 1997).

The purpose of this study was to derive equations using the Das-Naglieri: Cognitive Assessment System (CAS) for estimating pre-morbid intellectual functioning for school-aged children who have suffered a traumatic brain injury (TBI). This provides a method of estimating pre-morbid intellectual functioning that uses an assessment centered on a neuropsychological theory of intelligence and expands from existing pre-morbid intellectual functioning formulas.

Summary of the Study

A general overview of the equations created is first discussed, followed by a breakdown of analyses conducted to determine the usefulness of the equations. Next, each domain and full scale's respective equations and outcomes are then reviewed. Finally, a cross-validation sample with the 22 individuals with TBI is presented, ending with a short evaluation of the assumptions when estimating pre-morbid functioning.

The Das-Naglieri: Cognitive Assessment System standardization sample was utilized to create 17 regression equations that estimated both the CAS Domain score and Full Scale IQ. Procedures were similar to those used to create previous pre-morbid estimates based on the Wechsler scales (Schoenberg et al., 2004, 2007; Vanderploeg et al., 1996), utilizing top subtest predictors in combination with demographic variables to predict pre-morbid functioning. Predictors included CAS-subtests (both the best contributor and the top two contributors) as well as demographic variables (i.e., gender, race, and parent education level). One component that differed from other studies (except for Schoenberg et al., 2007) was the utilization of dummy-coded demographic variables so as not to unintentionally influence the analyses assigning numeric values to categorical variables (Tabachnick & Fidell, 2007).

Three equations were created to estimate each of the four CAS-Domain scores. This resulted in a total of 12 equations--three equations for each of the CAS-Domains of Planning, Attention, Simultaneous, and Successive. The equations included the top CAS-subtest in combination with demographic variables, the top two performing CAS-subtests in combination with demographic variables, and an equation utilizing demographic variables only in estimating pre-morbid CAS-Domains scores. For psychometric purposes and to remain consistent with other studies that utilized Full Scale IQ, an additional five equations were developed to estimate pre-morbid intellectual functioning for the CAS Full Scale IQ. Two equations utilized the top predicting CAS-Domain and top predicting CAS-subtest in combination with demographic variables to estimate pre-morbid intellectual functioning. Two additional equations combined the top two contributing CAS-Domains with demographic variables and the top two contributing CAS-subtests with demographic variables. The final equation estimated CAS Full Scale IQ using only the demographic variables.

Analysis of Equation

In general, the equations derived provided accurate estimates of both CAS-Domain Scores as well as CAS Full Scale IQ scores. All equations accounted for a significant amount of variance in actual CAS-Domain and IQ scores. The standard error of estimation (SEE) for demographic only variables was relatively high, though comparable with other pre-morbid equation studies, with a range from 13.63-14.39 for both the CAS-Domain and CAS Full Scale prediction equations. The SEE was significantly improved when demographic variables were combined with CAS measures with a range of 3.48-8.82. The lower SEE occurred in equations utilizing the top two best contributors from the CAS, both Domain and Subtests, in combination with demographic variables. The SEE for this group ranged from 3.48 to 5.56. The equations utilizing only the top CAS contributor in combination with demographic variables had SEE values ranging from 5.94 to 8.82. The SEE for the combination equations in this study were similar to those found in the Schoenberg et al. (2007) study that employed similar methods. As with similar studies, it appeared that utilizing both current assessment data and demographic data in estimating pre-morbid intellectual functioning might be the best practice in yielding accurate estimates.

When the equations were applied to the non-clinical validation sample, the mean estimated CAS-Domain and CAS Full Scale IQ scores did not significantly differ any equations, except for the Attention Estimate Equation 1 that utilized the top two CAS-subtests in combination with demographic variables to estimate the pre-morbid CAS-Attention domain score (p = .04). All combination equations approximated the CAS mean of 100 and a standard deviation of 15, while the demographic only variables approximated the CAS mean of 100 but had a standard deviation closer to 5. The majority of the equations (n = 10) had estimates of pre-morbid functioning within 10 points of the actual CAS-Domain and CAS Full Scale IQ scores. All equations that combined demographic variables with either top predicting CAS-Subtests or CAS-

Domains preformed significantly better than the demographic only counterparts. Thus, combination equations might be utilized prior to utilizing demographic only equations in estimating pre-morbid functioning.

This study went beyond previous studies by decomposing the pre-morbid equations and analyzing the results based on the child's age. These analyses provided information that will be useful in determining the appropriateness of the equation in specific age populations. In particular, some equations showed limitations in accurately estimating pre-morbid intellectual functioning, primarily for children aged 12 (seven equations total) and 14 (three equations total), although additional ages were represented with less than three equations resulting in significant differences in actual versus estimated scores (ages 5, 6, 7, 13, and 16). Analyses indicated that for 13 of the 17 equations, predicted scores differed significantly from the actual CAS-Domain or CAS Full Scale IQ scores ($p < .05$) for certain ages. All of the ages (5, 6, 7, 12, 13, 14, and 16) had at least one equation for each CAS-Domain and CAS Full Scale score that did not result in significant differences that would be appropriate to use in estimating pre-morbid intellectual functioning. For example, if the Attention Estimate Equation 1 resulted in significant differences in actual versus predicted CAS-Attention scores for seven-year-olds, Attention Estimate Equations 2 and 3 would still be valid options for estimating pre-morbid functioning in that age group. It should be noted that because all of these age groups had a small sample size ($n < 45$), further validation of the equations would be necessary to determine any true age discrepancies among the equations. All of these results showed promise in being effective methods of estimating pre-morbid intellectual functioning in children and adolescents.

Domain Estimation Equations

It appeared that all three equations--(a) two subtests and demographic variables; (b) one subtest and demographic variables, and (c) demographic variables only--created to estimate the Planning Domain were valid and appropriate to use when estimating pre-morbid intellectual functioning. Practitioners should use caution when interpreting the Planning Domain estimates for healthy individuals ages 12 and 14 until more information can be provided regarding the validity of these equations as they did produce significantly different values from estimated and actual scores (p = .021, p = .015 and p = .035).

Two out of the three equations created to estimate the Attention Domain were valid and appropriate to use when estimating pre-morbid intellectual functioning as evidenced by their predictive value in estimating pre-morbid intellectual functioning on the non-clinical validation sample. Attention Estimate Equation 1 (i.e., two subtests and demographic variables to estimate pre-morbid intellectual functioning) resulted in significant differences between actual and predicted scores for non-clinical individuals (p = .04). Practitioners should use caution when interpreting the Attention Domain estimates for Attention Estimate Equation 1, particularly for healthy individuals who are seven-years-old, until more information can be provided regarding the validity of these equations since they produced significantly different values from estimated and actual scores (p = .034).

Overall, all three equations worked well in estimating pre-morbid intellectual functioning in non-clinical individuals (p > .05) for the Simultaneous domain. As with the previous domains, practitioners should use caution when interpreting the

Simultaneous Domain estimates for all estimate equations, particularly for healthy individuals who are in the 12-16 year range, until further validation can be provided (p = .019, p = .005 and p = .024, respectively).

The results of the Simultaneous analyses supported the initial hypothesis that Figure Memory and Visual-Spatial Relations would be significant predictors in estimating pre-morbid intellectual functioning. This was consistent with Gutentag et al. (1998) who found no significant difference in test performance between healthy controls and individuals with TBI on the Figure Memory and Visual-Spatial Relations subtests.

Successive Domain equations appeared to work well in estimating pre-morbid intellectual functioning in non-clinical individuals as a whole (p > .05). However, Successive Estimate Equations 1 and 2--(a) two subtests and demographic variables and (b) one CAS subtest and demographic variables to estimate pre-morbid intellectual functioning--did result in significant differences in the 14-year-old sample (p = .044 and p = .012), meaning that caution in interpretation should be using those two equations in estimating pre-morbid intellectual functioning in 14-year-olds until further validation can be provided.

The results of the Successive analyses were consistent with the initial hypothesis that Word Series would be significant predictor of pre-morbid intellectual functioning. This also comported with Gutentag et al. (1998) who found no significant difference in test performance between healthy controls and individuals with TBI on the Word Series subtests.

Full Scale Estimation Equations

Both the Full Scale CAS-Subtest Estimate Equations and the Full Scale Demographic Estimate Equation worked well in estimating pre-morbid intellectual functioning in non-clinical individuals ($p > .05$) in that the estimated score did not significantly differ from the actual score across all ages in the non-clinical validation sample. The CAS-Subtest Estimate Equations used both the top two predictors from each CAS Domain (Full Scale CAs-Subtest Estimate Equation 1) and the single best CAS subtest predictor (Full Scale CAs-Subtest Estimate Equation 2) from each domain in combination with demographic variables to estimate pre-morbid intellectual functioning. The Full Scale Demographic equation used solely demographic variables in its estimation of pre-morbid intellectual functioning. Practitioners should use caution when interpreting the results of the Full Scale CAS-Subtest Estimate Equations 1 ($p = .015$) and 2 ($p = .003$), particularly for healthy individuals who are 12-years-old until more information can be provided regarding the validity of these equations as they did produce significantly different values from estimated and actual scores.

Full Scale CAS-Domain Estimate Equations 1 and 2--(a) two CAS-Domains in combination with demographic variables to estimate pre-morbid intellectual functioning and (b) one CAS-Domain in combination with demographic variables--worked well in estimating pre-morbid intellectual functioning in non-clinical individuals ($p < .05$) in that the estimated score did not significantly differ from the actual score across all ages in the non-clinical validation sample. Full Scale CAS-Domain Estimate Equation 1 appeared to be less effective at predicting Full Scale scores on healthy individuals aged six as it produced significantly different estimations from the actual score ($p = .035$). In addition, Full Scale CAS-Domain Estimate Equation 2 did not perform as well for healthy individuals who are 12-years-old for the same reason as Full Scale CAS-Domain Estimate Equation 1 (p = .024).

The results of best predictor CAS-domains, with the Planning domain as the strongest contributor, contrasted with the hypothesis that Planning and Attention would not make significant contributions to the equations to estimate pre-morbid intellectual functioning. However, it was hypothesized that the Successive Domain would be valuable in predicting pre-morbid intellectual functioning as was the case in this study.

Traumatic Brain Injury Cross-Validation Sample

The additional cross-validating utilized data from 22 individuals identified as having a TBI in the CAS standardization sample, which demonstrated that the average predicted score across all age levels (domain and full scale) differed significantly on all but 10 equations. Although not all equations resulted in significant differences for individuals with a TBI, it showed promise of the effectiveness of the equations in estimating pre-morbid intellectual functioning in clinical populations. It is possible with more research, including testing the equations on a significantly larger sample of children with TBI, that the differences between actual and predicted scores will be significant for all 17 equations. Although these results were promising for estimating pre-morbid intellectual functioning in children who have experienced a TBI, the findings should be considered tentative as larger cross-validation samples are needed.

Estimation Assumptions

All pre-morbid intellectual functioning equations must meet basic methodology assumptions as set forth by previous researchers (i.e., Schoenberg et al., 2007) in order to be deemed appropriate in assessing pre-morbid functioning in both healthy and clinical populations. As mentioned previously, when using the equations with healthy individuals, Schoenberg et al. (2007) suggested that the difference between the actual and estimated IQ score should not be significantly different. Further, they suggested that when using the equation with neurologically impaired individuals, the predictions should be greater than actual performance on IQ measures and the mean of the assumed predicted IQ scores of the clinical sample should estimate the mean of actual Full Scale IQ scores of healthy individuals (i.e., mean = 100, standard deviation = 15). In this study, the non-clinical validation sample confirmed the first component in validating a set of pre-morbid estimation equations by having no significant difference between estimated and actual scores. Sixteen out of the 17 equations resulted in no significant difference between the two scores (with the exception of the Attention Estimate Equation 1). In addition, the TBI validation group appeared to be near the general population's mean of 100 and a standard deviation of 15; however, due to the small sample size, more research is needed to further validate this assumption.

Implications

There are substantial theoretical and practical implications of this study. Theoretically, prior efforts at estimating pre-morbid IQ have relied heavily on atheoretical approaches such as the Wechsler scales and the Stanford-Binet. While new Wechsler scales have been developed, Naglieri and Kaufman (2001) contended that these refinements still failed to incorporate new theoretical approaches and only updated the material based on presentation and standardization data.

Alternatively, the Das-Naglieri: Cognitive Assessment System (Naglieri & Das, 1997) provided an assessment with strong theoretical underpinnings in neurological functioning modeled after Luria's (1966, 1973) model of cognitive processing. As such, it incorporates the assessment of three functional systems necessary for neurological processing, Planning, Attention, and Successive/Simultaneous processing (Luria, 1966, 1973).

This study provided the addition of utilizing the Das-Naglieri: Cognitive Assessment System in estimating pre-morbid intellectual functioning by offering estimation equations based on more neurologically sound assessments to the field of estimating pre-morbid intellectual functioning. This marked a great contribution to not only estimating pre-morbid intellectual functioning but to the field of assessment, evaluation, and education as well. It provided one more approach to an ever-growing field with hopes of linking assessment data to intervention, something that has yet to be accomplished in this domain.

The field of school psychology is constantly shifting and changing to incorporate new models and theories to support our practice. With the incorporation of Response to Intervention (RTI), there is a greater need to use theoretically tested and sound assessment measures when working with school-aged children. There needs to be a shift from using atheoretical methods of assessment, such as the Wechsler and Stanford-Binet cognitive assessments, toward a more theoretical, research driven assessment such as the Das-Naglieri: Cognitive Assessment System. This will assist in helping make sound education determinations when estimating pre-morbid intellectual functioning for children with a traumatic brain injury.

A variety of practical applications when using a theoretically sound assessment to estimate pre-morbid intellectual functioning in school-aged children are also noted from this study. The CAS incorporates evidence-based classroom interventions tied to test data, proving its utility above the Wechsler scale. Estimating pre-morbid intellectual functioning in a student who has a traumatic brain injury and being able to analyze current scores as compared to an estimated previous level of functioning can help in the selection and implementation of an intervention. No other assessment to date in estimating pre-morbid intellectual functioning has this ability.

For example, interventions have been studied to determine the effect on classroom interventions on individuals who show a cognitive weakness in the domain area of Planning. Naglieri and Gottling (1997) incorporated planning instruction in a math lesson and found that students who displayed poor planning benefited from planning instruction more than students who had strength in planning. This is just one example of many in which the CAS test data, specifically the comparison of current test performance to estimating previous levels of functioning, could help with intervention selection, implementation, and student progress.

The practice of estimating pre-morbid intelligence is slowly becoming more commonplace in the educational system and new benefits are still being discovered. There might be additional uses beyond the assistance for intervention selection in estimating pre-morbid intellectual functioning. Additional uses that have yet to be studied but hold promise include eligibility determination for special education and monitoring of recovery following a traumatic brain injury.

Limitations

One limitation of the current study was finding that children's cognitive skills could progress rapidly during the first six months following a neuropsychological insult (Dykeman, 2009). Thus, there is the chance of either over- or under-estimating the child's pre-morbid intellectual functioning as the time since injury elapses increases (Schoenberg et al., 2007). The time elapsed between injury and CAS administration for the 22 individuals with a reported TBI used in this study was unknown, necessitating the need to continue validating the 17 equations derived in this study. In accordance with the previous limitation, a study incorporating time-elapsed since injury into pre-morbid estimation equations might prove beneficial in providing even more accurate estimates in children with TBIs.

Another limitation of the current study was that the equations developed could not account for all variables that might impact the variance in an individual's PASS cognitive processes and overall cognition, e.g., location of injury, time elapsed since injury, and severity of injury (Harrington, 1990; Schoenberg et al., 2008). Again, this could result in an over- or under-estimation of the child's pre-morbid intellectual functioning and should be considered when interpreting the results from the equations.

A third limitation of the study was the number of cases with missing data. Although the cases with missing data appeared to be at random, there was always a chance that information in the missing data might skew the results of the analyses. The researcher attempted to remedy this by analyzing the data using the Expectation Maximization method of imputation to determine if cases with missing data contributed significantly to the results. Analyses indicated there were no drastic differences in the outcomes of the equations by using either deleting missing cases from the analyses or utilizing an imputation method.

A fourth limitation of the study was the age of the Cognitive Assessment System; using U.S. Census data from the early 1990s might or might not have accurately represented current population trends and data. Although the researcher attempted to compare the census data utilized for the standardization of the CAS to the most recent 2010 U.S. Census data, a similar breakdown of race was reported in the early 1990's. A limitation still exists in understanding the application of the CAS to the current U.S. population.

Most significantly, the small size of the TBI validation sample for the pre-morbid intellectual estimation equations posed a significant limitation in the ability to generalize equation estimates to clinical populations. Additional studies might be warranted to validate the equations with children who have suffered a neuropsychological injury such as traumatic brain injury.

Suggestions for Future Research

Future research would benefit in several ways to further refine methods of estimating pre-morbid intellectual functioning. First, as is necessary with other pre-morbid equations utilizing the Wechsler scales, future research should continue to validate the equations using a clinical sample. Ideally, a larger sample of children who have experienced a TBI, ranging in age from 5 to 17, would be necessary to fully validate the equations proposed in this study. Information on variables including time elapsed since injury, pre-morbid data (if available), and location and severity of injury would be necessary to provide a comprehensive understanding of the utility of the equations in a clinical population. Analyses should include performance of the equation depending on the severity, the location, and time elapsed to determine the appropriate administration of the equations in determining pre-morbid functioning in school-aged children. This would allow school practitioners to be well versed in the utility of the equations and determine appropriate intervention and placement as a result of the information provided by the estimates.

Finally, studies incorporating pre-morbid intellectual functioning in educational practices might yield valuable information for both clinicians and school practitioners in education decision-making and placement. With the new initiation of Response to Intervention (RTI), pre-morbid intellectual functioning might help in selecting and implementing evidence-based interventions. Determining the usefulness of having pre-morbid functioning data in the decision-making process might allow practitioners to implement appropriate interventions more rapidly than applying interventions haphazardly that might or might not prove beneficial for the child. In addition, having pre-morbid functioning estimates might allow proper placements in special education to further validate the educational impact of a traumatic brain injury.

Conclusion

This study set out to create pre-morbid functioning estimation equations using the Das-Naglieri: Cognitive Assessment System and served to augment the literature of estimating pre-morbid intellectual functioning in school-aged children. Evidence suggested that 16 of the 17 equations created in this study were valid and appropriate to use in estimating pre-morbid intellectual functioning as evidenced by the equations produced between estimated scores, which did not reliably differ from actual scores for

CAS-Domains and CAS Full Scale IQ. Further, it provided preliminary evidence that the equations might be effective in estimating pre-morbid intellectual functioning in clinical samples of children with a TBI.

A set of pre-morbid estimation equations could prove beneficial in the educational system to support educational based decision-making for both special education placement and for evidence-based intervention selection in the RTI process. The use of pre-morbid estimates in data based decision-making could help streamline the RTI process and special education placement decisions in order to best serve students reintegrating into the school system following a traumatic brain injury. Future research is needed to further validate the equations on a clinical sample of children with neurological deficits to determine the full utility and application of the 17 equations, as well as validate the utility of pre-morbid estimation in education systems. Data from this study could be cast along with other attempts in estimating pre-morbid intelligence when other data are not available.

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APPENDIX A

COGNITIVE ASSESSMENT SYSTEM ESTIMATE EQUATIONS

Planning Estimation Equation 1:
Planning domain = 43.914 + Matching Numbers Std. Score (2.972) + Planned Codes (2.537) + Gender + PEL + Race

Gender	male (.337)	female(nil)		
PEL	>HS(nil)	HS(1.103)	Some College(.861)	College grad(2.114)
Race	White(nil)	Black(-2.281)	Asian(-.544)	Other(-.246)
	Native A. (2.180)			

Planning Estimate Equation 2:
Planning domain = 59.211 + Matching Numbers Std. Score (4.073) + Gender + PEL + Race

Gender	male (-1.791)	female(nil)		
PEL	>HS(nil)	HS(1.444)	Some College(1.095)	College grad(2.799)
Race	White(nil)	Black(-3.123)	Asian(2.564)	Other(.499)
	Native A. (3.571)			

Planning Estimate Equation 3:
Planning domain = 98.237 + Gender + PEL + Race

Gender	male (-5.075)	female(nil)		
PEL	>HS(nil)	HS(3.904)	Some College(4.268)	College grad(7.717)
Race	White(nil)	Black(-4.181)	Asian(10.113)	Other(1.057)
	Native A. (-1.983)			

Attention Estimate Equation 1:
Attention = 45.577 + Receptive Attention Std. Score (3.074) + Expressive Attention Std. Score (2.427) + Gender + PEL + Race

Gender	male (-.552)	female(nil)		
PEL	>HS(nil)	HS(.089)	Some College(.109)	College grad(.397)
Race	White(nil)	Black(-.533)	Asian(.024)	Other(-1.276)
	Native A. (-.660)			

Attention Estimate Equation 2:
Attention = 60.095 + Receptive Attention Std. Score (3.979) + Gender + PEL + Race

Gender	male (-.702)	female(nil)		
PEL	>HS(nil)	HS(.481)	Some College(.888)	College grad(2.265)
Race	White(nil)	Black(-1.824)	Asian(1.294)	Other(.628)
	Native A. (-.781)			

Attention Estimate Equation 3:
Attention = 99.060 + Gender + PEL + Race

Gender	male (-5.363)	female(nil)		
PEL	>HS(nil)	HS(3.560)	Some College(4.356)	College grad(7.642)
Race	White(nil)	Black(-3.542)	Asian(8.267)	Other(1.159)
	Native A. (.810)			

Simultaneous Estimate Equation 1:
Simultaneous = 45.975 + Figure Memory Std. Score (2.782) + Visual-Spatial Relations (2.493) + Gender + PEL + Race

Gender	male (-.100)	female(nil)		
PEL	>HS(nil)	HS(.649)	Some College(1.125)	College grad(2.207)
Race	White(nil)	Black(-1.655)	Asian(1.617)	Other(.266)
	Native A. (-2.520)			

Simultaneous Estimate Equation 2:
Simultaneous = 60.716+ Figure Memory (3.677) + Gender + PEL + Race

Gender	male (-.082)	female(nil)		
PEL	>HS(nil)	HS(1.913)	Some College(3.215)	College grad(5.561)
Race	White(nil)	Black(-2.961)	Asian(.390)	Other(-.522)
	Native A. (-4.330)			

Simultaneous Estimate Equation 3:
Simultaneous = 95.814+Gender + PEL + Race

Gender	male (-.237)	female(nil)		
PEL	>HS(nil)	HS(4.250)	Some College(6.474)	College grad(12.577)
Race	White(nil)	Black(-9.171)	Asian(5.310)	Other(-2.961)
	Native A.(-3.439)			

Successive Estimate Equation 1:
Successive = 46.363 + Sentence Repetition (2.931) + Word Series (2.333) + Gender + PEL + Race

Gender	male (.048)	female(nil)		
PEL	>HS(nil)	HS(.515)	Some College(.558)	College grad(1.478)
Race	White(nil)	Black(.637)	Asian(.403)	Other(-.547)
	Native A. (-.209)			

Successive Estimate Equation 2:
Successive = 54.610 + Sentence Repetition Std. Score (4.411) + Gender + PEL + Race

Gender	male (.277)	female(nil)		
PEL	>HS(nil)	HS(.241)	Some College(.447)	College grad(1.509)
Race	White(nil)	Black(1.293)	Asian(1.636)	Other(-.631)
	Native A. (1.287)			

Successive Estimate Equation 3:
Successive = 96.200 + Gender + PEL + Race

Gender	male (-.823)	female(nil)		
PEL	>HS(nil)	HS(3.461)	Some College(6.146)	College grad(11.464)
Race	White(nil)	Black(-4.165)	Asian(-1.319)	Other(-6.063)
	Native A. (-1.393)			

Full Scale Demographic Equation 1:
Full Scale = 96.090 + Gender + PEL + Race

Gender	male (-3.765)	female(nil)		
PEL	>HS(nil)	HS(5.001)	Some College(7.050)	College grad(13.028)
Race	White(nil)	Black(-6.947)	Asian(7.181)	Other(-2.272)
	Native A. (-1.934)			

Full Scale CAS-Subtest Estimate 1:
Full Scale = 21.584 +Matching Numbers Std. Score (1.090) + Planned Codes (.915) + Receptive Attention Std. Score (1.096) + Expressive Attention Std. Score (.863) + Figure Memory Std. Score (.983) + Visual-Spatial Relations (.906) + Sentence Repetition Std. Score (1.050) + Word Series (.836) + Gender + PEL + Race

Gender	male (.276)	female(nil)		
PEL	>HS(nil)	HS(.397)	Some College(.374)	College grad(1.112)
Race	White(nil)	Black(-.780)	Asian(-.319)	Other(-.480)
	Native A. (-.168)			

Full Scale CAS-Subtest Estimate 2:
Full Scale = 33.727 + Matching Numbers Std. Score (1.620) + Receptive Attention Std. Score (1.589) + Figure Memory Std. Score (1.384) + Sentence Repetition Std. Score (1.916) + Gender + PEL + Race

Gender	male (-.061)	female(nil)		
PEL	>HS(nil)	HS(.514)	Some College(.700)	College grad(1.958)
Race	White(nil)	Black(-1.131)	Asian(.826)	Other(.572)
	Native A. (.467)			

Full Scale CAS-Domain Estimate 1:
Full Scale = -10.371 + Planning Domain Standard Score (.608) + Successive Domain Std. Score (.486) + Gender + PEL + Race

Gender	male (-.279)	female(nil)		
PEL	>HS(nil)	HS(.946)	Some College(1.469)	College grad(2.766)
Race	White(nil)	Black(-2.381)	Asian(1.674)	Other(.031)
	Native A. (-.052)			

Full Scale CAS-Domain Estimate 2:
Full Scale = 21.218 + Planning Domain Standard Score (.762) + Gender + PEL + Race

Gender	male (-.279)	female(nil)		
PEL	>HS(nil)	HS(2.025)	Some College(3.797)	College grad(7.146)
Race	White(nil)	Black(-3.760)	Asian(-.526)	Other(-3.078)
	Native A. (-.423)			

APPENDIX B

ARTICLE

Traumatic brain injury (TBI) is the world-wide leading cause of death and a significant cause of disabilities in children (Suominen et al., 1998). Using data from 2002-2006, the Centers for Disease Control reported that approximately 511,000 cases occurred per year for children from 0-14 years of age (Faul, Xu, Wald, & Coronado, 2010). Moreover, males are more likely than females to suffer a traumatic brain injury, with the ratio of injuries of males to female being approximately 2:1 between the ages of 5 and 14, with the greatest discrepancy between genders evident between the ages of 10 to 14 (Faul et al., 2010). Thus, TBI is a pervasive phenomenon in childhood.

The long-lasting effects of TBI for children, including cognitive and neuropsychological deficits have been well documented. TBI's result in attentional problems (Kaufmann, Fletcher, Levin, Miner, & Ewing-Cobbs, 1993), primarily in the areas of sustained and selective attention with displayed difficulties in the ability to focus attention, as well as sustaining and shift their attention resulting in long-lasting deficits in academic achievement (Ewing-Cobbs, Fletcher, Levin, Iovino, & Miner, 1998). With similar samples of children with TBI, other researchers have found that these children display significant deficits in executive functioning skills such as short-term memory and problem solving skills (Dennis, Wilkinson, Koski, & Humphreys, 1995; Hoffman, Donders, & Thompson, 2000). The reauthorization of Section 504 and the Rehabilitation act of 1973, IDEA (1990) included the category of traumatic brain injury (Russell, 1993) and is now recognized and used consistently in educational settings. Previously, most students with TBI were being labeled as "emotionally disturbed," learning disabled, other health impaired, or physically handicapped in order to receive services (D'Amato & Rothlisberg, 1996).

Pre-morbid intellectual functioning, or the level of functioning prior to an insult or injury to the brain, is valuable in determining the direct impact of the TBI and future directions for interventions and supports for the individual. Typically, clinicians estimate pre-morbid intellectual functioning because it provides a baseline in establishing the presence and magnitude of deficits that result from brain injury. Additionally, estimating pre-morbid functioning can be helpful for educators to select appropriate interventions and adjust progress monitoring measures to continually assess a child's functioning.

A variety of methods are used to estimate pre-morbid intellectual functioning including (a) clinical interview, (b) demographic regression formulas, (c) current test performance regression formulas, (d) combining demographic and current performance data, (e) historical test performance, and (f) combining historical test performance with demographic data. Determining appropriate methods for estimating pre-morbid intellectual functioning can be difficult, and the measures used should strongly correlate with the measured IQ of a healthy individual and must be resistant to neurological deficit and/or psychiatric disorder (Morris, Wilson, Dunn, & Teasdale, 2005).

Studies incorporating current assessment subtest and domain scores have historically used the Wechsler scales as their primary tool, including estimates using the Wechsler Adult Intelligence Scale-Revised (Vanderploeg, Schinka, & Axelrod, 1996), the Wechsler Adult Intelligence Scale-Third Edition (Schoenberg et al., 2004) and the Wechsler Intelligence Scale for Children – Fourth Edition (Schoenberg et al., 2007). These studies utilized the subtests of Picture Completion, Information, Vocabulary, and Matrix Reasoning as well as demographic variables of age in years, gender, and parent education level because of their demonstrated reliability and demonstrated utility in previous pre-morbid estimate equations (Schoenberg et al., 2007) such as that proposed by Barona and colleagues (1984). Demographic variables were included only if they contributed significantly to the estimation equation, with all equations incorporating at least one of the demographic variables if not all into the final estimation equation. Schoenberg et al (2008) tested the proposed equations using a clinical sample of children who sustained a TBI and found that all variables entered into the equation assisted in yielding accurate estimates of pre-morbid functioning as compared to a healthy control sample.

The inclusion of the atheoretical Wechsler scales in the estimate of pre-morbid intellectual functioning despite its popularity in the practice of IQ assessment, leaves perhaps much to be desired in view of modern theoretical, neuropsychological based perspectives of cognitive functioning that seem more connected to remedial efforts and positive outcomes, such as the Das-Naglieri Cognitive Assessment System (Naglieri & Das, 1997).

The age of previous intelligence assessments, such as Wechsler and Stanford Binet scales, have not allowed for the incorporation of recent discoveries of intelligence theories into our cognitive assessments, leaving them to be dated and potentially less effective in measuring children's abilities. Naglieri and Kaufman (2001) propose that not only are cognitive assessments such as Wechsler and Stanford Binet scales outdated but the content of the assessments were created prior to their prospective theories of intelligence, creating assessments that are weak in theoretical basis.

An alternative conceptualization of cognitive functioning was offered by A.R. Luria (1966, 1973) who proposed that human cognitive processes involved three functional systems that work together to create mental activity, or cognitive processes. Luria proposed a model of cognitive processing made up of three functional units that are necessary for mental activity (1966). He went on to describe the uniqueness and independence of each unit but also concluded that each functional unit depends on one another to function and perform effectively (Luria, 1980). Luria's work led to the conceptualization of the PASS (Planning, Attention, Simultaneous, and Successive; Das & Naglieri, 1995) model of cognitive functioning, often seen as an interactive and inter-reliant model of the construct of mental activity, which was further operationalized with an assessment tool known as the *Das-Naglieri: Cognitive Assessment System* (CAS; Naglieri & Das, 1997).

According to the authors, using the theoretical framework provided by the PASS model the CAS surpassed the constraints experienced by previous intelligence tests (Naglieri & Kaufman, 2001). The benefit of the PASS model over traditional models of intelligence is the incorporation of planning and attention domains, the two areas considered to be essential for cognitive functioning (Naglieri, 1997) and the two areas often impacted following a TBI (Hoffman et al., 2000).

The practice of estimating pre-morbid intellectual functioning on school aged children have many utilities including, but not limited to, determination of brain injury severity, assistance with intervention selections in the school and future outcomes for affected children. Few studies exist in estimating pre-morbid intellectual functioning in school aged children, with current studies relying heavily on the Wechsler intelligence assessments. The reality that only one set of equations stands out among the rest and are available for use with children, whose center intelligence assessment tool lacks the sensitivity to detect subtle deficits in this population (Naglieri, Das & Jarman, 1990) is being used to ascertain information about a child's outcome is concerning. Due to the theoretical limitations of the Wechsler scales, the inclusion of an assessment involving cognitive processes, such as the Cognitive Assessment System, should be considered in estimating pre-morbid intellectual functioning.

This study's purpose is to create an equation(s) that utilizes an assessment whose foundations center on a neuropsychological theory of cognitive processing, whose creation was theoretically driven, and has research linking assessment data to interventions. In addition, creating an equation(s) that expands from the already created pre-morbid intellectual functioning equations, such as the OPIE III for adults or the equations using WISC IV standardization data, whose basis lies in almost century old theories and practices will benefit both educators and practitioners in estimating pre-morbid intellectual functioning.

Method

Participants

Participants included 2,791 individuals with complete data from 3,072 subjects in the Das-Naglieri: Cognitive Assessment System (CAS) standardization sample. Demographic variables include age in years, parent education level and gender. The CAS standardization sample was selected to closely match the United States Census data on key demographic variables of gender, sex, geographic region, parent education level and race/ethnicity. Demographic characteristics of the CAS standardization sample are provided in the CAS Interpretive Manual (Naglieri & Das, 1997).

Measures and Procedure

The Das-Naglieri Cognitive Assessment System (CAS) is a cognitive assessment instrument that is normed according to United States Census data and is based on the PASS theory. The CAS provides four domain scores, namely Planning, Attention, Simultaneous and Successive (PASS) as well as a Full Scale (FS) score comprised of all four domains for psychometric purposes. Each domain and the FS score is organized with a mean of 100 (*SD* = 15). The four domain areas are formed through the contribution of 12 subtests (mean = 10; *SD* = 3). The number of subtests administered (12 total) depends on the battery given: a standard battery includes the complete 12 subtests, while the basic battery requires eight subtests. Additional psychometric properties of the CAS can be found in the interpretive handbook (Naglieri & Das, 1997). The manual reports adequate to high reliability coefficients along with validity studies conducted during its development.

The CAS standardization sample was divided into two random groups after removing the individuals with a reported TBI (*n* = 22). The first group was used to create the equations (development group, *n* = 2,492) and the second was used to validate the equations (non-clinical validation group, *n* = 277). The remaining 22 individuals with a reported TBI were utilized in a preliminary analysis of the effectiveness of the equations with a clinical sample. Differences between the development group and the non-clinical validation group for age, race, parent education level, gender, as well as Full Scale, domain. and subtest scores were analyzed using a one-way analysis of variance.

As the CAS is comprised of four domain areas which according to the PASS theory have a unique relationship of being independent, yet they are independent, it is difficult to determine which domains and/or subtests may be the best predictors in estimating overall (FS) pre-morbid intellectual functioning. Thus, a stepwise method of multiple linear regression was utilized due to the exploratory nature of this study and the fact that this is the first known study that uses the Cognitive Assessment System in estimating pre-morbid intellectual functioning. Once the top predicting CAS subtests and CAS domains were revealed, a series of enter regression analyses were conducted to create the algorithms.

A total of 17 equations were generated to predict pre-morbid intellectual functioning at the Domain score and Full Scale IQ level. Five regression equations incorporated only the demographic variables of gender, parent education level, and race, one for each domain and Full Scale score. Four equations were generated incorporating the two subtests that provided the most predictive value (e.g., Matching Numbers and Planned Codes), in combination with demographic variables (i.e., gender, parent education level and race) to predict each domain and Full Scale score separately. Five equations were generated incorporating the single best subtest predictor in combination with demographic variables in estimating domain and full scale scores. Finally, two equations were created to predict the Full Scale score using the best domain in predicting the full scale score in combination with demographic variables, and using the top two domain predictors in combination with demographic variables.

So as not to influence the contribution of the categorical variables based on arbitrarily assigned numbers variables for gender, parent education level, race, were each dummy coded (see Schoenberg et al., 2007, for a similar approach). In the creation of the demographic only equations, all demographic variables were entered into the equation.

For subsequent models (both subtest and domain), each top predicting subtest or domain variable was entered first into the equation, followed by each of the demographic variables.

The final stage of analysis consisted of cross-validating the generated equations using the non-clinical validation sample (10% of the standardization sample) as well as the small sub-sample of children with a identified TBI (n = 22) as a preliminary analysis of the utility of the equations.

Results

Descriptive statistics and analysis of variance analyses for demographic variables and CAS measures between the development and non-clinical group are presented in Tables 1 and 2. There were no statistically significant differences between the groups on any of the demographic variables (i.e., gender, age, and parent education level), CAS subtests, CAS domains, and Full Scale scores.

Table 1

Descriptive Statistics of Demographic Variables by Cognitive Assessment System Group

	Development (*n* = 2492)		Non-Clinical (*n* = 277)		TBI (*n* = 22)	
Variable	N	%	n	%	N	%
Gender						
Male	1209	48.5	118	42.6	14	36.4
Female	1283	51.5	159	57.4	8	63.6
Race						
White	1930	77.4	218	78.7	21	95.5
Black	308	12.4	36	13	1	4.5
Asian	11	.4	2	0.7		
Native Am.	126	5.1				
			12	4.3		
Other	117	4.7	9	3.2		
Age						
5	244	9.8	25	9		
6	350	14	43	15.5		
7	372	14.9	38	13.7		
8	257	10.3	30	10.8		
9	221	8.9	28	10.1	1	4.5
10	231	9.3	27	9.7	3	13.6
11	152	6.1	15	5.4	4	18.2
12	110	4.4	12	4.3		
13	140	5.6	14	5.1	3	13.6
14	117	4.7	18	6.5	6	27.3
15	108	4.3	11	4	1	4.5
16	97	3.9	6	2.2	3	13.6
17	93	3.7	10	3.6	1	4.5

Table 2

Means and Standard Deviations of Cognitive Assessment System Scaled Scores: Development and Non-Clinical Validation

Variable		Development		Non-clinical Validation		1-Way ANOVA	
Domain	Subtest	*M*	*SD*	*M*	*SD*	*F*-Ratio	*p*
Planning		100.11	15.46	100.62	14.42	0.27	.60
	Matching Numbers(MN)	9.95	3.09	10.00	2.85	0.09	.76
	Planned Codes(PD)	10.09	2.99	10.01	2.79	0.18	.67
	Planned Connect(PN)	10.041	3.00	10.30	2.87	1.91	.17
Attention		100.68	14.98	99.78	15.39	0.91	.34
	Expressive Attention(EA)	10.05	3.08	10.17	2.87	0.36	.55
	Number Detection (ND)	10.14	3.01	10.01	3.05	1.67	.20
	Receptive Attention(RA)	10.07	3.03	9.90	2.99	0.83	.36
Simultaneous		101.16	14.92	100.47	15.05	0.54	.46
	Nonverbal Matrices(MT)	10.15	3.00	10.21	3.11	0.08	.77
	Verbal-Spatial Rel. (SV)	10.26	3.01	9.77	2.96	3.76	.05
	Figure Memory (FM)	10.32	3.06	10.18	3.06	0.43	.51
Successive		100.75	15.16	99.50	14.72	1.70	.19
	Word Series (WS)	10.10	3.07	9.87	2.94	1.40	.24
	Sentence Repetition(SR)	10.24	2.96	10.03	3.03	1.16	.28
	Sentence Questions(SQ)	10.23	3.09	10.02	2.93	1.13	.29
	Speech Rate (SSR)	10.11	3.04	9.99	2.82	0.35	.55
Full Scale		100.53	15.43	99.74	15.13	0.64	.42
Parent Education Level		13.46	1.91	13.40	1.91	0.19	.67
Age (in years)		9.42	3.47	9.33	3.37	0.17	.68

A summary of all of the equations generated from the development group (*n* = 2492) are presented in Table 3 and the equations are presented in their entirety at the end of the article. The demographic information accounted for approximately 16% of the variance for the Full Scale equation, while accounting for 9.4% to 16.8% of the variance on the domain equations. The equations comprising both two best CAS predictors and demographic variables accounted for 87.3 to 94.9% of the variance. Equations that combined demographic variables and the single best CAS predictor accounted for 67%-75% of the overall variance in the model. It should be noted that all the subtests that entered into the equation (with the exception of the Receptive Attention-RA and Visual-Spatial Relations-SV) are all of the subtests that can be administered for the CAS Basic Battery. This can extend the utility of the equations by not requiring examiners to administer the full battery but rather the basic battery with the addition of two subtests, Receptive Attention and Visual-Spatial Relations.

Table 3

Regression results Summary for Estimating Full Scale and Domain Scores From Demographic Variables and Cognitive Assessment System Subtest/Domain Standard Scores

Regression Model	R^2	SEE	*F*
Full Scale Score			
Full Scale Demographic Estimate Eq. 1	0.16	14.16	59.51**
Full Scale CAS-Subtest Estimate Eq. 1	0.95	3.48	2907.83**
Full Scale CAS-Subtest Estimate Eq. 2	0.86	5.94	1196.27**
Full Scale CAS-Domain Estimate Eq. 1	0.87	5.56	1669.20**
Full Scale CAS-Domain Estimate Eq. 2	0.69	8.64	606.56**
Planning			
Planning Estimate Equation 1	0.90	4.96	2172.71**
Planning Estimate Equation 2	0.72	8.82	711.12**
Planning Estimate Equation 3	0.10	14.72	33.134**
Attention			
Attention Estimate Equation 1	0.89	4.95	2034.05**
Attention Estimate Equation 2	0.69	8.43	599.10**
Attention Estimate Equation 3	0.09	14.28	32.17**
Simultaneous			
Simultaneous Estimate Equation 1	0.87	5.32	1709.28**
Simultaneous Estimate Equation 2	0.67	8.58	561.49**
Simultaneous Estimate Equation 3	0.17	13.63	62.47**
Successive			
Successive Estimate Equation 1	0.90	4.90	2136.94**
Successive Estimate Equation 2	0.76	7.50	853.77**
Successive Estimate Equation 3	0.10	14.39	34.92**

NOTE: N = 2492. ** $p < .001$. CAS = Cognitive Assessment System; SEE = standard error of estimate; Full Scale Demographics Estimate Eq. 1= demographic only equation; Full Scale CAS-Subtest Estimate Eq. 1 = equation utilizing Matching Numbers, Planned Codes, Receptive Attention, Expressive Attention, Figure Memory, Visual-Spatial Relations, Sentence Repetition and Word Series subtest standard scores + demographic variables to predict Full Scale IQ; Full Scale CAS-Subtest Estimate Eq. 2 = equation utilizing Matching Numbers, Receptive Attention, Figure Memory and Sentence Repetition standard scores + demographic variables to predict Full Scale IQ; Full Scale CAS-Domain Estimate Eq. 1 = equation utilizing Planning and Successive domain standard scores and demographic variable to predict Full Scale IQ s; Full Scale CAS-Domain Estimate Eq. 2 = equation utilizing Planning Domain standard scores and demographic variables to predict Full Scale IQ; Planning Estimate Equation 1 = equation utilizing Matching Numbers and Planned Codes standard scores + demographic variables to predict Planning Domain score; Planning Estimate Equation 2 = equation utilizing Matching Numbers standard score + demographic variables to predict Planning Domain score; Planning Estimate Equation 3 = demographic only; Attention Estimate Equation 1 = equation utilizing Expressive Attention and Receptive Attention subtest standard scores + demographic variables to predict Attention Domain score; Attention Estimate Equation 2 = equation utilizing Receptive Attention subtest standard scores + demographic variables to predict Attention Domain score; Attention Estimate Equation 3 = demographic only to estimate Attention; Simultaneous Estimate Equation 1 = equation utilizing Figure Memory and Visual-Spatial Relations subtest standard scores + demographics to predict Simultaneous Domain score; Simultaneous Estimate Equation 2 = equation utilizing Figure Memory subtest standard score + demographics to predict Simultaneous Domain score; Simultaneous Estimate Equation 3 = demographic only to estimate Simultaneous domain score; Successive Estimate Equation 1 = equation utilizing Sentence Repetition and Word Series subtest standard score + demographics to predict Successive Domain score; Successive Estimate Equation 2 = equation utilizing Sentence Repetition subtest standard score + demographics to predict Successive Domain score; Successive Estimate Equation 3 = demographic only to predict Successive Domain score.

. To evaluate the accuracy of the equations, the 17 equations were cross-validated with the non-clinical validation sample as well as the TBI validation sample. Validation once again confirms the estimated accuracy of the developed equations by utilizing a sub-sample of the CAS standardization data to test the equations using real data. The assessment and demographic data from the two validation groups (10% of the cases and the TBI sample) were individually entered into the previously created equation(s) and then analyzed to determine accuracy of predicted versus actual scores. Data for each group (i.e., control and TBI) were analyzed using paired-samples t-tests. For the control sample, if the derived equation(s) accurately predicts FSIQ as well as performance on the various domain measures, then there should not be a statistically significant difference between the earned and estimated scores. However, for the TBI sample, it is expected that predicted scores on each measure will be significantly greater than the actual scores.

Following these analyses of the validation groups, the information derived is compared to prior research and theoretical expectations to determine how the equation(s) performs compared to other pre-morbid estimators. Each of the 277 non-clinical sample and the 22 TBI sample data were entered into each of the 17 equations. A total of five predicted Full Scale scores were estimated, along with three predicted CAS-domain scores for each domain (12 in total).

For the non-clinical validation sample, the average predicted score across all age levels (domain and full scale) did not significantly differ on all equations except for the equation utilizing the top two Attention CAS-subtests to predict the Attention domain score (Attention Estimate Equation 2, $t(276) = -2.065$, $p=.04$); meaning that all equations were effective in estimating pre-morbid intellectual functioning in the non-clinical sample by having predicted scores that did not differ significantly from the actual scores. Table 4 shows the equation, minimum and maximum values, and the relative *t* value and *p* values.

Table 4

Descriptive Statistics, Mean Comparisons and Significance Results Between Actual and Predicted Values for Domain and Full Scale Cognitive Assessment System Results

	Non-Clinical Validation Sample						
Actual IQ	Mean	SD	Min	Max	*P*	df	t
Full Scale	99.747	15	56	143			
Planning	100.62	14	61	139			
Attention	99.779	14	63	150			
Simultaneous	100.47	15	62	142			
Successive	99.501	14	59	139			
Predicted IQ							
Full Scale Demographic Est. Eq. 1	100.10	6.17	85	116	0.654	276	-0.448
Full Scale CAS-Subtest Est. Eq. 1	99.69	14.92	57	139	0.812	276	0.238
Full Scale CAS-Subtest Est. Eq. 2	99.74	14.07	56	135	0.994	276	0.007
Full Scale CAS-Domain Est. Eq. 1	100.18	14.07	57	134	0.184	276	-1.33
Full Scale CAS-Domain Est. Eq. 2	100.65	12.44	69	134	0.062	276	-1.871
Planning Est. Equation 1	100.10	13.39	69	144	0.059	276	1.899
Planning Est. Equation 2	100.19	12.14	70	133	0.37	276	0.898
Planning Est. Equation 3	99.61	4.51	88	116	0.213	276	1.248
Attention Est. Equation 1	**100.4**	**13.81**	61	150	**0.04**	**276**	**-2.065**
Attention Est. Equation 2	99.88	12.06	71	137	0.817	276	-0.232
Attention Est. Equation 3	100.19	4.36	90	114	0.614	276	-0.505
Simultaneous Est. Equation 1	100.13	13.66	68	135	0.296	276	1.048
Simultaneous Est. Equation 2	100.62	12.4	71	132	0.785	276	-0.274
Simultaneous Est. Equation 3	100.95	6.24	86	113	0.55	276	-0.598
Successive Est. Equation 1	99.61	14.34	62	137	0.674	276	-0.42
Successive Est. Equation 2	99.33	13.51	60	131	0.697	276	0.389
Successive Est. Equation 3	100.65	4.92	89	107	0.159	276	-1.411

*NOTE: Bold lines indicate predicted scores that are significantly different than the actual score.

To further analyze the accuracy of the predicted scores, a paired sample t-test was conducted for each individual age group to determine which equations are most appropriate depending on the age of the individual. All predicted scores did not differ from the actual score for each age group except for the following age/equation combination displayed in Table 5. Although some equations result in significantly different predicted values than actual values, it does appear that each age group has at least one equation from each of the CAS-Domain and Full Scale categories that can be utilized to predict domain and full scale scores. Further investigation is necessary, potentially with a larger sample size, to determine the validity of the equations in Table 5 in combination with the age groups in question.

Table 5

Analyses of Cognitive Assessment System Pre-morbid Equation Accuracy by Age

Regression Model	Age	df	Actual (Mean)	Predicted (Mean)	t	*P*
Full Scale CAS-Subtest Est. Eq. 1	12	11	86	88	2.882	.015
Full Scale CAS-Subtest Est. Eq. 2	12	11	86	89	3.857	.003
Full Scale CAS-Domain Est. Eq. 1	6	42	103	101	-2.182	.035
Full Scale CAS-Domain Est. Eq. 2	12	11	86	93	2.612	.024
Planning Est. Equation 1	12	11	93	95	-2.695	.021
Planning Est. Equation 2	12	11	93	97	-2.88	.015
Planning Est. Equation 3	14	17	106	101	2.294	.035
Attention Est. Equation 1	7	37	96	98	-2.196	.034
Simultaneous Est. Equation 1	5	24	105	102	2.521	.019
Simultaneous Est. Equation 2	12	11	87	94	-2.627	.005
	16	5	86	94	-5.581	.002
Simultaneous Est. Equation 3	12	11	87	98	-2.627	.024
	13	13	108	101	2.433	.03
	16	5	86	98	-3.405	.019
Successive Est. Equation 1	14	17	106	104	2.117	.044
Successive Est. Equation 2	14	17	106	102	2.793	.012

Additional cross-validation analyses on the non-clinical validation sample to determine the differences between predicted and actual standard scores on the following criteria: (a) ±5 points, (b) ±10 points, and (c) same category. Analyses that are comparable to those reported in other studies assessed pre-morbid intellectual functioning equations (i.e., Schoenberg et al., 2007). The analyses are displayed in Table 6. In this case, predicted scores were categorized into three categories (a) ±5 points, (b) ±10 points, and (c) same category and again show comparability to similar studies of estimating pre-morbid intellectual functioning.

Table 6

Predictive Accuracy of Estimations of Full Scale and Domain Scores: Non-clinical Validation Sample

	Percentage Within		
Equation	±5	±10	Same Category
Full Scale Demographic Est. Eq. 1	25.3	53.1	42.2
Full Scale CAS-Subtest Est. Eq. 1	87	99.6	85.2
Full Scale CAS-Subtest Est. Eq. 2	65	94.2	71.1
Full Scale CAS-Domain Est. Eq. 1	65.7	93.5	66.4
Full Scale CAS-Domain Est. Eq. 2	50.2	81.2	59.2
Planning Est. Equation 1	75.5	97.1	75.8
Planning Est. Equation 2	50.2	79.8	57
Planning Est. Equation 3	25.6	50.2	46.6
Attention Est. Equation 1	77.6	95.7	31
Attention Est. Equation 2	48.7	85.2	35
Attention Est. Equation 3	30	54.9	52.3
Simultaneous Est. Equation 1	62.1	93.1	69.3
Simultaneous Est. Equation 2	39.7	70.8	49.5
Simultaneous Est. Equation 3	28.5	52.3	40.1
Successive Est. Equation 1	73.3	96.8	72.6
Successive Est. Equation 2	50.5	81.6	63.5
Successive Est. Equation 3	29.2	55.6	53.4

Discussion

The Das-Naglieri: Cognitive Assessment System standardization sample was utilized to create 17 regression equations that estimated both the CAS Domain score and CAS Full Scale IQ. Procedures were similar to those used to create previous pre-morbid estimates based on the Wechsler scales (Schoenberg et. al., 2004, 2007; Vanderploeg et al., 1996), utilizing top subtest predictors in combination with demographic variables to predict pre-morbid functioning. Predictors included CAS-subtests (both the best contributor and the top two contributors), as well as demographic variables (i.e., gender, race and parent education level). One component that differed from other studies (but see Schoenberg et. al., 2007) was the utilization of dummy coded demographic variables so as not to unintentionally influence the analyses assigning numeric values to categorical variables.

Three equations were created to estimate each of the four CAS-Domain scores. This resulted in a total of 12 equations--three equations for each of the CAS-Domains of Planning, Attention, Simultaneous and Successive. The equations included the top CAS-subtest in combination with demographic variables, the top two performing CAS-Subtests in combination with demographic variables and an equation utilizing demographic variables only in estimating pre-morbid CAS-Domains scores. For psychometric purposes and to remain consistent with other studies that utilize full scale IQ, an additional five equations were developed to estimate pre-morbid intellectual functioning for the CAS Full Scale IQ. Two equations utilized the top predicting CAS-Domain and top predicting CAS-subtest in combination with demographic variables to estimate pre-morbid intellectual functioning. Two additional equations combined the top two contributing CAS-Domains with demographic variables and the top two contributing CAS-Subtests with demographic variables. The final equation estimated CAS Full Scale IQ using only the demographic variables. Cross-validation of the equations was accomplished utilizing 10% of the CAS standardization sample as well as 22 individuals with a known TBI.

In general, the equations derived provided accurate estimates of both CAS-Domain Scores as well as CAS Full Scale IQ scores. All equations accounted for a significant amount of variance in actual CAS-Domain and IQ scores. The standard error of estimation (SEE) for demographic only variables was relatively high, though comparable with other pre-morbid equation studies, with a range from 13.63-14.39 for both the CAS-Domain and CAS Full Scale prediction equations. The SEE was significantly improved when demographic variables were combined with CAS measures with a range of 3.48-8.82. The lower SEE occurred in equations utilizing the top two best contributors from the CAS, both Domain and Subtests, in combination with demographic variables. The SEE for this group ranged from 3.48 to 5.56. The equations utilizing only the top CAS contributor in combination with demographic variables had SEE values ranging from 5.94 to 8.82.

When the equations were applied to the non-clinical validation sample the mean estimated CAS-Domain and CAS Full Scale IQ scores did not significantly differ any equations, except for the Attention Estimate Equation 1 that utilized the top two CAS-Subtests in combination with demographic variables to estimate pre-morbid CAS-Attention domain score (p=.04). All combination equations approximated the CAS mean of 100 and a standard deviation of 15, while the demographic only variables approximated the CAS mean of 100 but had a standard deviation closer to 5. The majority of the equations (n = 10) had estimates of pre-morbid functioning within 10 points of the actual CAS-Domain and CAS Full Scale IQ scores. All equations that combined demographic variables with either top predicting CAS-Subtests or CAS-Domains preformed significantly better than the demographic only counterparts. Thus, combination equations may be utilized prior to utilizing demographic only equations in estimating pre-morbid functioning.

This study went beyond previous studies by decomposing the pre-morbid equations and analyzing the results based on the child's age. These analyses provided information that will be useful in determining the appropriateness of the equation in specific age populations. In particular, some equations showed limitations in accurately estimating pre-morbid intellectual functioning, primarily for children aged 12 (seven equations total) and 14 (three equations total), although additional ages were represented with less than three equations resulting in significant differences in actual versus estimated scores (ages 5, 6, 7, 13, and 16). Analyses indicated that for 13 of the 17 equations, predicted scores differed significantly from the actual CAS-Domain or CAS Full Scale IQ scores ($p < .05$) for certain ages. All of the ages (5, 6, 7, 12, 13, 14, and 16) had at least one equation for each CAS-Domain and CAS Full Scale Score that did not result in significant differences that would be appropriate to use in estimating pre-morbid intellectual functioning. For example, if the Attention Estimate Equation 1 resulted in significant differences in actual versus predict CAS-Attention scores for seven year olds, Attention Estimate Equations 2 and 3 are still valid options for estimating pre-morbid functioning in that age group). It should be noted that because all of these age groups had a small sample size ($n < 45$), further validation of the equations will be necessary to determine any true age discrepancies among the equations. All of these results show promise in being effective methods of estimating pre-morbid intellectual functioning in children and adolescents.

It appears that all three equations created to estimate the Planning Domain are valid and appropriate to use when estimating pre-morbid intellectual functioning. Practitioners should use caution when interpreting the Planning Domain estimates for healthy individuals ages 12 and 14 until more information can be provided regarding the validity of these equations as they did produce significantly different values from estimated and actual scores ($p < .05$).

Two out of the three equations created to estimate the Attention Domain are valid and appropriate to use when estimating pre-morbid intellectual functioning as evidenced by their predictive value in estimating pre-morbid intellectual functioning on the non-clinical validation sample. Attention Estimate Equation 1 resulted in significant differences between actual and predicted scores for non-clinical individuals ($p < .05$). Practitioners should use caution when interpreting the Attention Domain estimates for Attention Estimate Equation 1, particularly for healthy individuals who are seven years old, until more information can be provided regarding the validity of these equations as they produced significantly different values from estimated and actual scores ($p < .05$).

Overall, all three equations work well in estimating pre-morbid intellectual functioning in non-clinical individuals ($p > .05$) for the Simultaneous domain. As with the previous domains, practitioners should use caution when interpreting the Simultaneous Domain estimates for all estimate equations, particularly for healthy individuals who are in the 12-16 year range, until further validation can be provided ($p < .05$). The results of the Simultaneous analyses support the initial hypothesis that Figure Memory and Visual-Spatial Relations would be significant predictors in estimating pre-morbid intellectual functioning. This is consistent with Gutentag, Naglieri, and Yeates (1998) who found no significant difference in test performance between healthy controls and individuals with TBI on the Figure Memory and Visual-Spatial Relations subtests. Successive Domain equations appear to work well in estimating pre-morbid intellectual functioning in non-clinical individuals as a whole ($p > .05$). However, the equation did result in significant differences in the 14-year-old sample ($p < .05$), meaning that caution in interpretation should be utilized. The results of the Successive analyses are consistent with the initial hypothesis that Word Series would be significant predictor of pre-morbid intellectual functioning. This also comports with Gutentag et al. (1998) who found no significant difference in test performance between healthy controls and individuals with TBI on the Word Series subtests.

Both the Full Scale CAS-Subtest Estimate Equations and the Full Scale Demographic Estimate Equation work well in estimating pre-morbid intellectual functioning in non-clinical individuals ($p > .05$) in that the estimated score does not significantly differ from the actual score across all ages in the non-clinical validation sample. Practitioners should use caution when interpreting the results of the Full Scale CAS-Subtest Estimate Equations 1 and 2, particularly for healthy individuals who are 12 years old until more information can be provided regarding the validity of these equations as they did produce significantly different values from estimated and actual scores ($p < .05$).

Full Scale CAS-Domain Estimate Equations 1 and 2 work well in estimating pre-morbid intellectual functioning in non-clinical individuals ($p < .05$) in that the estimated score does not significantly differ from the actual score across all ages in the non-clinical validation sample. Full Scale CAS-Domain Estimate Equation 1 appears to be less effective at predicting Full Scale scores on healthy individuals aged six, as it produced significantly different estimations from the actual score($p < .05$). In addition, Full Scale CAS-Domain Estimate Equation 2 did not perform as well for healthy individuals who are 12 years old for the same reason as Full Scale CAS-Domain Estimate Equation 1($p < .05$).

The additional cross-validation utilizing data from 22 individuals identified as having a TBI in the CAS standardization sample demonstrated the average predicted score across all age levels (domain and full scale) differed significantly on all but 10 equations. Although these results are promising for estimating pre-morbid intellectual functioning in children who have experienced a TBI, the findings should be considered tentative as larger cross-validation samples are needed.

All pre-morbid intellectual functioning equations must meet basic methodology assumptions as set forth by previous researchers (i.e., Schoenberg et al., 2007) in order to be deemed appropriate in assessing pre-morbid functioning in both healthy and clinical populations. As mentioned previously, when using the equations with healthy individuals, Schoenberg et al. (2007) suggest that the difference between the actual and estimated IQ score should not be significantly different. Further, they suggest that when using the equation with neurologically impaired individuals the predictions should be greater than actual performance on IQ measures and the mean of the assumed predicted

IQ scores of the clinical sample should estimate the mean of actual Full Scale IQ scores of healthy individuals (i.e., mean = 100, standard deviation = 15). In this study, the non-clinical validation sample confirmed the first component in validating a set of pre-morbid estimation equations by having no significant difference between estimated and actual scores. 16 out of the 17 equations resulted in no significant difference between the two scores (with the exception of the Attention Estimate Equation 1).

Implications

There are substantial theoretical and practical implications of this study. Theoretically, prior efforts at estimating pre-morbid IQ have relied heavily on atheoretical approaches, such as the Wechsler scales and the Stanford-Binet. While new Wechsler scales have been developed, Naglieri and Kaufman (2001) contend that these refinements still fail to incorporate new theoretical approaches and only update the material based on presentation and standardization data.

Alternatively, the Das-Naglieri: Cognitive Assessment System (Naglieri & Das, 1997) provides an assessment with strong theoretical underpinnings in neurological functioning, modeled after Luria’s model of cognitive processing. As such, it incorporates the assessment of three functional systems necessary for neurological processing, Planning, Attention, and Successive/Simultaneous processing (Luria, 1966, 1973).

This study provides is the addition of utilized the Das-Naglieri: Cognitive Assessment System in estimating pre-morbid intellectual functioning offering estimation equations based on a more neurologically sound assessment to the field of estimating pre-morbid intellectual functioning. This marks a great contribution to not only estimating pre-morbid intellectual functioning, but to the field of assessment, evaluation and education as well. It provides one more approach to an ever growing field with hopes of linking assessment data to intervention, something that has yet to be accomplished in this domain.

The practice of estimating pre-morbid intelligence is slowly becoming more commonplace in the educational system and new benefits are still being discovered. There may be additional uses beyond the assistance for intervention selection in estimating pre-morbid intellectual functioning. Additional uses that have yet to be studied but hold promise include eligibility determination for special education and monitoring of recovery following a traumatic brain injury.

Limitations

One limitation of the current study is the finding that children's cognitive skills can progress rapidly during the first six months following a neuropsychological insult (Dykeman, 2009). Thus, there is the chance of either over- or under-estimating the child's pre-morbid intellectual functioning as the time since injury elapses increases (Schoenberg et al., 2007). The time elapsed between injury and CAS administration for the 22 individuals with a reported TBI used in this study is unknown, necessitating the need to continue validating the 17 equations derived in this study. In accordance with the previous limitation, a study incorporating time-elapsed since injury into pre-morbid estimation equations may prove beneficial in providing even more accurate estimates in children with TBIs.

Another limitation of the current study is that the equations developed cannot account for all variables that may impact the variance in an individual's PASS cognitive processes and overall cognition, such as location of injury, time elapsed since injury and severity of injury (Schoenberg et al., 2008; Harrington, 1990). Again, this can result in an over- or under-estimation of the child's pre-morbid intellectual functioning and should be considered when interpreting the results from the equations.

Most significantly, the small size of the TBI validation sample for the pre-morbid intellectual estimation equations poses a significant limitation in the ability to generalize equation estimates to clinical populations. Additional studies may be warranted to validate the equations with children who have suffered a neuropsychological injury such as traumatic brain injury.

Suggestions for Future Research

Future research should further refine methods of estimating pre-morbid intellectual functioning. First, as is necessary with other pre-morbid equations utilizing the Wechsler scales, future research should continue to validate the equations using a clinical sample. Ideally, a larger sample of children who have experienced a TBI, ranging in age from 5 to 17, would be necessary to fully validate the equations proposed in this study. Information on variables including time elapsed since injury, pre-morbid data (if available), as well as location and severity of injury would be necessary to provide a comprehensive understanding of the utility of the equations in a clinical population. Analyses should include performance of the equation depending on the severity, the location, as well as time elapsed to determine the appropriate administration of the equations in determining pre-morbid functioning in school-aged children.

Finally, studies incorporating pre-morbid intellectual functioning in educational practices may yield valuable information for both clinicians and school practitioners in education decision making and placement. With the new initiation of Response to Intervention (RTI) pre-morbid intellectual functioning may help in selecting and implementing evidence based interventions. Determining the usefulness of having pre-morbid functioning data in the decision making process may allow practitioners to implement appropriate interventions more rapidly than applying interventions haphazardly that may or may not prove beneficial for the child. In addition, having pre-morbid functioning estimates may allow proper placements in special education to further validate the educational impact of a traumatic brain injury.

Conclusion

This study set out to create pre-morbid functioning estimation equations using the Das-Naglieri: Cognitive Assessment System and will serve to augment the literature of estimating pre-morbid intellectual functioning in school-aged children. Evidence suggests that 16 of the 17 equations created in this study are valid and appropriate to use in estimating pre-morbid intellectual functioning as evidenced by the equations producing between estimated scores and that did not reliably differ from actual scores for CAS-Domains and CAS Full Scale IQ. Further, it provides preliminary evidence that the equations may be effective in estimating pre-morbid intellectual functioning in clinical samples of children with a TBI.

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Planning Estimation Equation 1:
Planning domain = 43.914 + Matching Numbers Std. Score (2.972) + Planned Codes (2.537) + Gender + PEL + Race

Gender male (.337) female(nil)
PEL >HS(nil) HS(1.103) Some College(.861) College grad(2.114)
Race White(nil) Black(-2.281) Asian(-.544) Other(-.246) Native A. (2.180)

Planning Estimate Equation 2:
Planning domain = 59.211 + Matching Numbers Std. Score (4.073) + Gender + PEL + Race

Gender male (-1.791) female(nil)
PEL >HS(nil) HS(1.444) Some College(1.095) College grad(2.799)
Race White(nil) Black(-3.123) Asian(2.564) Other(.499) Native A. (3.571)

Planning Estimate Equation 3:
Planning domain = 98.237 + Gender + PEL + Race

Gender male (-5.075) female(nil)
PEL >HS(nil) HS(3.904) Some College(4.268) College grad(7.717)
Race White(nil) Black(-4.181) Asian(10.113) Other(1.057) Native A. (-1.983)

Attention Estimate Equation 1:
Attention = 45.577 + Receptive Attention Std. Score (3.074) + Expressive Attention Std. Score (2.427) + Gender + PEL + Race

Gender male (-.552) female(nil)
PEL >HS(nil) HS(.089) Some College(.109) College grad(.397)
Race White(nil) Black(-.533) Asian(.024) Other(-1.276) Native A. (-.660)

Attention Estimate Equation 2:
Attention = 60.095 + Receptive Attention Std. Score (3.979) + Gender + PEL + Race

Gender male (-.702) female(nil)
PEL >HS(nil) HS(.481) Some College(.888) College grad(2.265)
Race White(nil) Black(-1.824) Asian(1.294) Other(.628) Native A. (-.781)

Attention Estimate Equation 3:
Attention = 99.060 + Gender + PEL + Race

Gender male (-5.363) female(nil)
PEL >HS(nil) HS(3.560) Some College(4.356) College grad(7.642)
Race White(nil) Black(-3.542) Asian(8.267) Other(1.159) Native A. (.810)

Simultaneous Estimate Equation 1:
Simultaneous = 45.975 + Figure Memory Std. Score (2.782) + Visual-Spatial Relations (2.493) + Gender + PEL + Race

Gender male (-.100) female(nil)
PEL >HS(nil) HS(.649) Some College(1.125) College grad(2.207)
Race White(nil) Black(-1.655) Asian(1.617) Other(.266) Native A. (-2.520)

Simultaneous Estimate Equation 2:
Simultaneous = 60.716+ Figure Memory (3.677) + Gender + PEL + Race

Gender male (-.082) female(nil)
PEL >HS(nil) HS(1.913) Some College(3.215) College grad(5.561)
Race White(nil) Black(-2.961) Asian(.390) Other(-.522) Native A. (-4.330)

Simultaneous Estimate Equation 3:
Simultaneous = 95.814+Gender + PEL + Race

Gender male (-.237) female(nil)
PEL >HS(nil) HS(4.250) Some College(6.474) College grad(12.577)
Race White(nil) Black(-9.171) Asian(5.310) Other(-2.961) Native A.(-3.439)

Successive Estimate Equation 1:
Successive = 46.363 + Sentence Repetition (2.931) + Word Series (2.333) + Gender + PEL + Race

Gender male (.048) female(nil)
PEL >HS(nil) HS(.515) Some College(.558) College grad(1.478)
Race White(nil) Black(.637) Asian(.403) Other(-.547) Native A. (-.209)

Successive Estimate Equation 2:
Successive = 54.610 + Sentence Repetition Std. Score (4.411) + Gender + PEL + Race

Gender male (.277) female(nil)
PEL >HS(nil) HS(.241) Some College(.447) College grad(1.509)
Race White(nil) Black(1.293) Asian(1.636) Other(-.631) Native A. (1.287)

Successive Estimate Equation 3:
Successive = 96.200 + Gender + PEL + Race

Gender male (-.823) female(nil)
PEL >HS(nil) HS(3.461) Some College(6.146) College grad(11.464)
Race White(nil) Black(-4.165) Asian(-1.319) Other(-6.063) Native A. (-1.393)

Full Scale Demographic Equation 1:
Full Scale = 96.090 + Gender + PEL + Race

Gender male (-3.765) female(nil)
PEL >HS(nil) HS(5.001) Some College(7.050) College grad(13.028)
Race White(nil) Black(-6.947) Asian(7.181) Other(-2.272) Native A. (-1.934)

Full Scale CAS-Subtest Estimate 1:
Full Scale = 21.584 +Matching Numbers Std. Score (1.090) + Planned Codes (.915) + Receptive Attention Std. Score (1.096) + Expressive Attention Std. Score (.863) + Figure Memory Std. Score (.983) + Visual-Spatial Relations (.906) + Sentence Repetition Std. Score (1.050) + Word Series (.836) + Gender + PEL + Race

Gender male (.276) female(nil)
PEL >HS(nil) HS(.397) Some College(.374) College grad(1.112)
Race White(nil) Black(-.780) Asian(-.319) Other(-.480) Native A. (-.168)

Full Scale CAS-Subtest Estimate 2:
Full Scale = 33.727 + Matching Numbers Std. Score (1.620) + Receptive Attention Std. Score (1.589) + Figure Memory Std. Score (1.384) + Sentence Repetition Std. Score (1.916) + Gender + PEL + Race

Gender male (-.061) female(nil)
PEL >HS(nil) HS(.514) Some College(.700) College grad(1.958)
Race White(nil) Black(-1.131) Asian(.826) Other(.572) Native A. (.467)

Full Scale CAS-Domain Estimate 1:
Full Scale = -10.371 + Planning Domain Standard Score (.608) + Successive Domain Std. Score (.486) + Gender + PEL + Race

Gender	male (-.279)	female(nil)			
PEL	>HS(nil)	HS(.946)	Some College(1.469)	College grad(2.766)	
Race	White(nil)	Black(-2.381)	Asian(1.674)	Other(.031)	Native A. (-.052)

Full Scale CAS-Domain Estimate 2:
Full Scale = 21.218 + Planning Domain Standard Score (.762) + Gender + PEL + Race

Gender	male (-.279)	female(nil)			
PEL	>HS(nil)	HS(2.025)	Some College(3.797)	College grad(7.146)	
Race	White(nil)	Black(-3.760)	Asian(-.526)	Other(-3.078)	Native A. (-.423)

APPENDIX C

INSTITUTIONAL REVIEW BOARD APPROVAL

UNIVERSITY of
NORTHERN COLORADO
Institutional Review Board (IRB)

December 20, 2011

TO: Carol Roehrs
Nursing

FROM: Maria Lahman, Co-Chair
UNC Institutional Review Board

RE: Expedited Review of Proposal, *Estimating Pre-Morbid Intellectual Functioning \ Using the Das-Nagliere: Cognitive Assessment System,* submitted by Amy Rhodes Research Advisor: Achilles Bardos)

First Consultant: The above proposal is being submitted to you for an expedited review. Please review the proposal in light of the Committee's charge and direct requests for changes directly to the researcher or researcher's advisor. If you have any unresolved concerns, please contact Maria Lahman, Applied Statistics and Research Methods, Campus Box 124, (x1603). When you are ready to recommend approval, sign this form and return to me.

with suggested changes.

I recommend approval ~~as is~~. Carol Roehrs Dec 20, 2011
Signature of First Consultant / Date

The above referenced prospectus has been reviewed for compliance with HHS guidelines for ethical principles in human subjects research. The decision of the Institutional Review Board is that the project is approved as proposed for a period of one year: 1-17-12 to 1-17-13.

1-17-12
Maria Lahman, Co-Chair Date

Comments:

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