THESIS

THE TEST OF EVERYDAY ATTENTION FOR CHILDREN: A CONFIRMATORY FACTOR ANALYSIS APPROACH

Submitted by

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ABSTRACT

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As the incidence of children diagnosed with Autism Spectrum Disorders (ASD) and Attention Deficit Hyperactivity Disorder (ADHD) continues to grow, the need for objective measures of attentional performance is clearly warranted for evaluating attentional differences and guiding intervention. This study examined the multidimensional nature of attention. Previous research suggests that there may be three types of attention: selective attention, control shift attention, and sustained attention. One hundred and eleven children age six to twelve completed the nine subtests of the Test of Everyday Attention for Children (TEA-Ch, Manly, Robertson, Anderson & Nimmo-smith, 1999). Using a confirmatory factor analysis approach, this study sought to determine whether a three-factor model, as supported in a prior confirmatory factor analysis study with Australian children (Manly, Nimmo-Smith, Watson, Anderson, Turner, & Robertson, 2001), could be replicated with an American sample, or alternatively if a four factor model, with the addition of divided attention, would better explain the covariance structure of this study's data. An additional objective addressed in this study was whether the three-factor model could be

ii

improved by using raw scores while taking the effects of age and gender into account compared the three factor model using scaled scores. A two factor model was also explored due to high correlations between the latent factors in the three factor model.

Confirmatory factor analysis indicated that a two-factor model using age-scaled scores best explained the covariance structure in this sample's data, χ^2 (26, N=111) = 34.65, p = .120, NFI = .79, NNFI = .89, CFI = .92. Whereas, the three-factor model using age-scaled scores was less desirable, χ^2 (24, N=111) = 34.63, p = .074, NFI = .79, NNFI = .86, CFI = .91. Although not as strong as some of the comparative fit indices of the Manly et al. (2001) normative study, overall the indices of fit of this study's two-factor model yielded a better solution than the three-factor model. These results suggest that selective attention and control shift attention may not reflect separate constructs of attention as shown in the Manly, et al. (2001) study. Additionally, the use of age-scaled scores in the three-factor model was superior to raw scores with age and gender controlled, χ^2 (24, N=111) = 42.07, p = .013, NFI = .71, NNFI = .75, CFI = .83. Furthermore, the four-factor model using age-scaled scores, χ^2 (21, N=111) = 34.25, p = .034, NFI = .79, NNFI = .81, CFI = .89 was also less desirable than the two-factor model using age-scaled scores.

Because this study confirms the ability to assess multidimensional aspects of attention, the TEA-Ch may be a valuable tool for practitioners and researchers. However, one possible drawback of the TEA-Ch is the hour required for children to complete its nine subtests. A briefer screening tool of the first four subtests of the TEA- Ch is suggested when time constraints arise. However, further analysis is recommended to determine if the four subtests in the TEA-Ch screening tool are optimal. Thus, additional research is needed with respect to shorter multidimensional assessments of attention to inform intervention and consequently improve the quality of life for children with attentional differences.

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TABLE OF CONTENTS

INTRODUCTION	. 1
Attention	. 1
Neuronatomy of Attention	.3
Development of Regulation and Attentional Systems	. 5
Individual Differences in Attention	.8
The Test of Everyday Attention for Children1	1
Psychometrics and Neuropsychological Assessments1	12
Reliability and Validity of the Test of Everyday Attention for Children1	٤4
Statistical Analysis1	L 7
Testing a Model of Attention using TEA-Ch Scores1	۱9
Conceptual Rationale for Using Raw Scores Controlling for Age and Gender2	21
PURPOSE	22
METHODS2	23
Participants2	24
Materials2	25
Procedures2	28
RESULTS	32
The Replication Model3	33
The Four-Factor Model3	38
The Two-Factor Model4	12

One-Factor Model	
Three-Factor Models with Raw Scores	47
Factor Loading and Correlation Comparison	
DISCUSSION	53
Models Using Raw Scores	57
Two-Factor Model	
Limitations	60
Conclusion	62
REFERENCES	

INTRODUCTION

With the increasing incidence of childhood diagnoses such as Attention Deficit Disorder (ADHD), Asperger's Syndrome, and Traumatic Brain Injury (TBI) symptoms of attentional difficulties are often noted and of considerable concern (Manly et al., 2001). By understanding the similarities and differences of attention deficit disorders among these populations, improved specificity of intervention is likely to result. Traditionally, attentional functioning in children has been assessed through cognitive, behavioral, and emotional questionnaires, such as the Conners Third Edition (Conners, 2004). However, more objective performance measures appear to be warranted to improve accuracy and specificity of diagnosing attentional differences across various populations. The Test of Everyday Attention for Children (TEA-Ch, Manly et al., 1999) is one such performance instrument that attempts to measure three distinct aspects of attention.

Attention

Attention is commonly defined as an individual's ability to concentrate or sustain focus on a task. Historically, attention has been described as a filtering system that sifts through large amounts of information to allow selected information to be perceived (Broadbent, 1958). More recently however, greater complexity is observed through

neural imaging studies which provided evidence that attention is conducted through a distinct "network of anatomical areas" (Posner & Peterson, 1990, p. 26). With respect to these specialized areas of the brain, a three-system perspective of attention was developed and included the terms orienting, alerting, and target detection (Posner & Peterson, 1990). Orienting refers to both overt visual orienting and the initial covert shifting of attention to a location (Posner & Peterson, 1990). Alerting denotes the ability of the individual to "prepare and sustain alertness" (Posner & Peterson, 1990, p. 35) when processing priority information. In target detection the attention system moves from a generalized alert state to a more highly engaged state when locating a visual target (Posner & Peterson, 1990).

Additional researchers agree with this multi-component perspective of attention, but instead name the three elements of attention focus, sustain, and shift (Mirsky, Anthony, Duncan, Ahearn, & Kellam, 1991). Focus is similar to target detection mentioned by Posner and Peterson (1990) as both equate with the ability to select a target from a display of stimuli (Mirsky et al., 1991). Sustained attention is the ability to maintain focus over time or vigilance (Mirsky et al., 1991) and can be related to alerting. Attentional shift refers to the ability to flexibly and adaptively adjust focus (Mirsky et al., 1991) and correlates well with the subsystem of orienting (see Table 1).

Posner & Peterson (1990)	Mirsky et al. (1990)	Manly et al.(2001)	
Target Detection	Focus	Selective Attention	
Alerting	Sustain	Sustained Attention	
Orienting	Shift	Attentional Control/Shift	

Table 1Different labels for types of attention used by various authors.

A fourth subsystem or element of attention, divided attention, is also discussed in the literature of neuropsychology and refers to the ability to focus on all pertinent stimuli concurrently (Cooley & Morris, 1990). Given these descriptions of the differentiated nature of attention, it is easy to see the incompleteness of our initial definition. Thus, instead of being a general state of awareness, attention may consist of multiple sub-processes. To continue our understanding of the multi-dimensional and complex nature of attention, an overview of the neuroanatomy of attention will now be provided.

Neuronatomy of Attention

Several studies support the viewpoint that the attentional system of the brain is specialized, localized, and interconnected (Cooley & Morris, 1990; Posner & Peterson, 1990; Mirsky et al., 1991). The human brain can be grossly divided into three regions: the forebrain, the midbrain, and the hindbrain. Through neural imaging studies, the attentional systems are currently believed to be located in the cerebrum of the forebrain (Posner & Peterson, 1990). The cerebrum is divided into two hemispheres, right and left, and within these two hemispheres are various pairs of lobes. First are the frontal lobes that are situated anteriorly. The parietal lobes are then located behind the two frontal lobes and at the back of the brain are the occipital lobes. The temporal lobes are then found beneath the frontal and parietal lobes. Near the center of the brain, within the inner brain or diencephalon, the thalamus and hypothalamus are found.

Through primate and human lesion studies, the posterior aspect of the parietal lobes, the posterior lateral aspect of the thalamus, and the superior colliculus, located within the inner brain, have been found to be active in coordinating orienting also known as attentional shift (Posner & Peterson, 1990). In more recent human lesion studies, the process of attentional shifting or switching has also been observed in the prefrontal cortex, located anteriorly within the frontal lobes (Shallice, Stuss, Picton, Alexander, & Gillingham, 2008).

In cerebral blood flow studies, the anterior cingulate, located just beneath the frontal lobes, was noted to be especially active during target detection (Posner & Peterson, 1990). More specifically, the anterior cingulate is believed to mediate response selection and modulate stimulus selection (Bush et al., 1999).

With respect to vigilance, the right cerebral hemisphere and possibly more specifically the right prefrontal cortex appear to be associated with the ability to initiate and sustain attention (Posner & Peterson, 1990). Manly, Robertson, Galloway, and Hawkins (1998) also reported that the ability to sustain attention relies on adequate functioning of the right prefrontal lobe. More recent sustained counting tasks performed with human lesion subjects, not only supported, but added accuracy to this theory. Shallice, Stuss, Alexander, Picton and Derkzen (2007) found that the right prefrontal cortex and the anterior cingulate do "play key roles in attention," (p. 804) but instead of controlling sustained attention, the process of initiation or energizing was shown to be a more precise description.

From the neuroanatomical discussion above, it is easy to see the specialization and interconnection of the attentional system as processing occurs anteriorly, laterally, and interiorly throughout the brain. This theme often reappears in the literature of neuropsychology as researchers continue to notice the differing characteristics of attention that correspond to a variety of separate brain locations (Manly et al., 1999). Having discussed the multi-faceted nature of attention and its anatomical diversity, our next discussion will focus on the development of attention.

Development of Regulation and Attentional Systems

Research in cognitive psychology believes that attention is the result of the collective processes of self-control (Posner & Rothbart, 2000). Self-control or more technically speaking, self-regulation describes the nature of volition in relationship with genetics and social experiences (Posner & Rothbart, 2000). Self-regulation with respect to attentional control is then defined as a characteristic of regulation whereby a person calmly organizes incoming stimuli in order to "delay gratification, tolerate change, and create an appropriate cognitive and behavioral response" (Muris, Mayer, van Lint, &

Hofman, 2008, p. 1496). Two processes that allow for attentional control are selection, or orienting, as discussed previously, and executive control respectively.

Selection refers to orienting one's visual attention to or shifting visual attention toward a sensory stimulus or location and is known to develop during the first year of life (Posner & Rothbart, 2000). Recent evidence of visual shift attention developing in infancy is noted in the literature of cognitive neuroscience. Error detection is one way to measure self-regulation (Posner, Rothbart, & Sheese, 2007) and through an EEG study of 7-month-old infants, increased anterior cingulate activity was noted when infants were shown an error scenario (Berger, Tzur, & Posner, 2006). Executive control is defined as the child's ability to act independently from his or her sensory world and can be thought of as a "supervisory attention system" (Posner & Rothbart, 2000, p.431). Executive control begins to develop during the second year of life (Posner & Rothbart, 2000). Measurement of executive attention through a location and identity conflict task was performed with children ages 24 to 36 months. Through this study, inhibitory control was found to begin to appear in children around 30 months (Gerardi-Caulton, 2000). Posner and Rothbart (2000) additionally stated that measurements of inhibitory control positively correlated with a child's level of self-control as reported by a parent. Regarding the relationship between attention and self-regulation, Manly et al. (1999) explained that attention develops as the child improves in his or her ability "to override

innate response tendencies and replace them with more flexible and appropriate ones" (p. 31).

Adding to our discussion of self-regulation, recent literature suggests that the attention system supports effortful control and that both may predict a child's ability to regulate his or her emotions (Simonds, Kieras, Rueda, & Rothbart, 2007). Effortful control denotes the child's internal ability to refrain from initiating an action to a dominant response in order to act upon a sub-dominant response (Rothbart & Rueda, 2005). Therefore, effortful control is the individuality of executive attention or temperament of the individual which influences emotional reactivity and consequently behavior and socialization (Posner & Rothbart, 2000). Two longitudinal studies with children between the ages of 32-66 months and 9 to 45 months suggest that effortful control begins to demonstrate consistency and stability around 30 months on performance tasks (Kochanska, Murray, Jacques, Koenig, & Vandegeest, 1996; Kochanska, Murray, & Coy, 1997). This correlation between inhibitory control and effortful control in various studies, both beginning to appear at 30 months, is developmentally meaningful and adds to the reliability of this particular finding. Effortful control is also believed to support emotional modulation and thus allows a child to express socially appropriate emotions and inhibit less desirable emotions (Eisenberg, Fabes, Guthre, & Reiser, 2000). According to Eisenberg, Smith, Sadovsky,

and Spinrad (2004) emotional regulation is dependent on one's ability to divert attention away from a stimulus that produces an undesired emotional state.

Moving from self-regulation to selective attention, Shepp, Barrett, and Kolbet (1987) found in a card sorting task that children demonstrated increases "in attentional control with increasing age" (p. 159). Regarding this developmental aspect of attention, Posner and Rothbart (2000) endorsed that executive attention as a whole "continues to develop throughout the early school years" (p. 434). Additionally, Manly et al. (1999) confirmed that attentional development increases in different patterns for separate areas of attention throughout childhood. To this point, the multidimensional, anatomically diverse, and developmental characteristics of attention have been addressed. A discussion regarding individual differences with respect to these attentional features follows.

Individual Differences in Attention

One of the most discussed diagnoses related to attentional differences is attention deficit hyperactivity disorder (ADHD, DSM IV, American Psychiatric Association, 1994). ADHD is defined by symptoms of inattention, hyperactivity, and impulsivity that significantly disrupt voluntary control of behavior in cognitive, social, and emotional areas (Barnes, J. Howard, D. Howard, Kenealy, & Vaidya, 2010). ADHD is believed to occur in 3.0-7.5% of school aged children and has a high prevalence of heritability as noted in recent family, adoption, and twin studies (Castellanos & Tannock, 2002). Also, severe early deprivation, family psychosocial adversity, and maternal smoking during pregnancy have been found to be significant environmental risk factors for ADHD (Castellanos & Tannock, 2002). Three subtypes of ADHD are mentioned in diagnostic manuals and include predominantly inattentive, predominantly hyperactive-impulsive, and combined types (DSM IV, American Psychiatric Association, 1994). With respect to attention, poor sustained attention stands out as a characteristic of ADHD; however, research indicates that this limitation is secondary with respect to impaired inhibitory control (Barkly, 1997; Manly et al, 2001). Furthermore, recent research on ADHD identifies that difficulties in self-regulation and executive functioning are just as significant as difficulties in attention (Barkley, 2007).

In returning to neuroanatomy with respect to ADHD, various researchers have narrowed in on the anterior cingulate as an area that demonstrates attentional differences. In normal subjects, the anterior cingulate shows increased blood flow prior to cognitive tasks and is thus believed to play a role in anticipation and preparation (Murtha, Cherkow, Beauregard, Dixon, & Evans, 1996). Additionally, other researchers reported that the anterior cingulate is also activated during tasks requiring selfregulation (Posner et al., 2007). Interestingly, anatomical pathway differences were found in a fMRI study with adults diagnosed with ADHD where during conflict resolution

tasks, anterior cingulate activity did not increase as it did in control participants, but instead activity increases were observed in the anterior insula (Bush, et al., 1999).

Attentional difficulties, however, do not occur solely in the ADHD population, but are also observed in children with acquired or neurological disorders such as epilepsy, learning disabilities, depression, Autism, and in children prescribed medical treatments such as chemotherapy or epilepsy medication (Cooley & Morris, 1990). Additional researchers also include "Asperger's syndrome, Traumatic Brain injury, Tourettes syndrome, Insulin Dependent Diabetes, Anxiety Disorder and Post Traumatic Stress Disorder" (Manly et al., 1999, p. 31) as diagnoses that frequently demonstrate attentional differences. Continuing along this line of thinking, Manly et al. (1999) proposed that attentional deficits tend to be varied across disability groups due to cerebral pathology and/or timing of the onset of a particular health condition. Therefore, as attentional differences have been observed among a variety of disorders, the ability to directly assess the separate components of attention may provide significant information regarding the underlying processing differences associated with specific diagnoses. This information may then be instrumental in diagnosing and guiding intervention.

The Test of Everyday Attention for Children

The Test of Everyday Attention for Children (TEA-Ch) is a standardized, normed assessment adapted from the adult battery entitled the Test of Everyday Attention (TEA, Manly et al., 1999). By adopting a three-system perspective of attention, the TEA-Ch attempts to assess and quantify attentional ability. The terms selective attention, sustained attention, and attentional control/switching are used within the TEA-Ch to describe the assessment's areas of focus. Selective attention can be compared with the focus element of Mirsky et al. (1991) or the target detection system discussed by Posner and Peterson (1990) and is defined as "the ability to resist distraction, to sort through information, and to discriminate elements that are important to the task" (Manly et al., 1999, p. 5). Sustained attention is similar to the alerting system described by Posner and Peterson (1990) and is defined as "the ability to keep one's mind on a job" (Manly et al., 1999, p.5). Attentional control/switching is representative of orienting and attentional shift in the above-mentioned perspectives and denotes a person's ability to shift attention evenly from one task to another (Manly et al., 1999). Additionally, the TEA-Ch assesses divided attention as discussed by Cooley and Morris (1990) within two of its subtests specified as dual task measures.

As mentioned above, attention is very likely not a single process (Manly et al., 1999). Therefore, the attention systems require a variety of differentiated tasks to accurately assess each system individually (Manly et al., 2001). The TEA uses 8 subtests

to determine an adult's (age 18-80 years) pattern of strengths and weaknesses across the three attentional categories through visual and auditory tasks (Crawford, Sommerville, & Robertson, 1997). The TEA-Ch also uses visual and auditory tasks to determine a child's (age 6-16 years) attentional strengths and weaknesses, but has 9 subtests instead of eight (Manly et al., 1999). Sustained attention performance is assessed across 5 subtests and selective attention and attentional control/switching are each assessed across 2 subtests (Manly et al., 2001). Two subtests organized within the sustained attention subtests additionally assess divided attention (Manly et al., 2001). The TEA-Ch also has a screening procedure whereby a clinician may select to have a client complete the first four subtests only as an estimate of performance across the four attention factors if time constraints are of concern (Manly et al., 1999). The TEA also includes a short form for use in the cases of fatigue, sensory disability, or time constraint (Crawford et al., 1997). Following this overview of the TEA-Ch, a discussion regarding the psychometrics of testing follows to improve understanding of this aspect of our assessment of interest.

Psychometrics and Neuropsychological Assessments

Neuropsychological assessments place strong emphasis on determining an individual's "pattern of relative strengths and weaknesses" (Crawford & Sommerville, 1997, p. 610). However, in order to determine an individual's ability with respect to a measure of performance, the question of an assessment's validity must first be answered. Four categories of validity are often described in the psychometric literature: predictive, concurrent, content, and construct validity. Predictive and concurrent validity are considered criterion-oriented validity whereby the researcher is using certain criteria to establish an association between the measure and an outcome (Cronbach & Meehl, 1955). Predictive validity refers to a measurement's ability to predict future performance (Portney & Watkins, 2009). Concurrent validity then, is when a measurement being examined is given at the same time as a reference measurement in order to assess the same behavior (Portney & Watkins, 2009). The ability of items within an assessment to adequately reflect the content being measured is content validity (Portney & Watkins, 2009). Whereas, a test's ability to measure a theoretical construct represents construct validity (Portney & Watkins, 2009).

In addition to assessment validity, it is important to know that the test instrument is stable and able to measure performance consistently and reliably (Portney & Watkins, 2009). To determine test-retest reliability, subjects are given a test on two occasions within a few days of each other and results are analyzed to derive test-retest coefficients (Portney & Watkins, 2009). Reliability coefficient values range from 1.0, meaning the measurement was without error to 0, meaning the measurement variation was completely due to error (Portney & Watkins, 2009). Thus, reliability is the measure of consistency or direct relationship of the test scores obtained in each of the two assessment sessions. With increased cognizance of validity and reliability of

measurements, a combined discussion of these concepts with respect to the TEA-Ch follows.

Reliability and Validity of the Test of Everyday Attention for Children

The TEA was standardized on 154 healthy adults and additional tables have been provided to clinicians for determining an "individual's profile of subtest strength and weaknesses" (Crawford et al., 1997, p. 609). The TEA-Ch was standardized on 293 Australian children (Manly et al., 1999). From a random sample of children seen between 5 and 20 days following their first assessment, reliability measures of testretest correlation coefficients for 7 of the 9 subtests ranged from .57 to .87 (Manly et al., 1999). "Where ceiling effects make correlations unrealistic, the percentage of agreement within 1 standard deviation (3 age-scaled points) for the first and second test is given" (p. 34) and ranged from 71% to 76.2% (Manly et al., 1999). With respect to validity, the associations between the observed scores in the TEA-Ch and the three factors of selective attention, sustained attention, and attentional control/switching were examined through confirmatory factor analysis that provided a number of measures of fit of the hypothetical model to the observed data (Manly et al., 1999). This type of measurement model allows the researcher to show relationships between subtests that measure a common process (Manly et al., 2001). Fit index values of .9 and above are deemed indicative of a good fit to the data (Hair, Anderson, Tatham, & Black, 1995). All three incremental fit measures were above .9; the Comparative Fit Index

equaled .973, the Normed Fit Index equaled .913, and the Non-Normed Fit Index equaled .96 (Manly et al., 1999).

Regarding content validity, several of the subtests of the TEA-Ch are based on historically referenced and validated tests. For example, the Sky Search and Map Mission subtests that assess selective attention by requiring an individual to find target stimuli within similar stimulus distracters is based on Wright and Vlietstra's developmental research that used similar systematic searches (Manly et al., 1999). Another of the subtests, Score!, one of the sustained attention tasks, is "a children's version of a well validated approach to assessing sustained attention in adults" (Manly et al., 1999, p. 32; Wilkins, Shallice, & McCarthy, 1987). Additionally, the Creature Counting subtest for attentional control switch is modeled after the Wisconsin Card Sorting Test (Manly et al., 1999).

Further testing for criterion-concurrent validity is provided in the Sky Search and Map Mission subtests that measure selective attention. Through additional testing of 96 of the children from the normative sample, statistically significant relationships were seen when comparing the Sky Search (r = .40, p < .001) and Map Mission (r = .31, p < .01) data to the Stroop task. Statistically significant relationships were also seen between Sky Search (r = .69, p < .001) and Map Mission (r = .37, p < .001) and the Trails Test A (Manly et al., 1999). Manly et al. (1999) also emphasized that the Creature Counting (Time) subtest of attentional control/switching factor does not show a statistically significant association with section Trails A of the Trails Test (r = .19, p > .05), but does demonstrate a significant association with the attentional switching task of Trails B (r = 21, p < .05).

Continuing our discussion of the psychometrics of the TEA-Ch assessment, the attribute or construct we are concerned with is specifically attention. Therefore, in order to determine if the TEA-Ch is a valid test of attention, two conditions are necessary based on the causal theory of measurement. First, the construct or attribute of interest must exist and second, variation in an attribute must cause variation in the observed performance score (Borsboom, Mellenbergh, & Heerden, 2004). Through neuropsychological research and theories cited previously, the existence of the construct of attention and its multi-dimensionality can be supported. In fact, Heaton, Reader, Preston, Fennell, Puyana, Gill, & Johnson (2001) stated that one of the advantages of the TEA-Ch is the "inclusion of multiple components of attention" (p. 254). Then with respect to the causality of the variability of an attribute to the variability of test scores, Manly et al. (1999) demonstrated that differences in attention of disability groups, ADHD and traumatic brain injury, caused differences in performance scores of attention. Age was also found to effect the variability of the test scores (Manly et al., 2001). Additionally, by reducing the confounding variables of memory, reading, writing, and motor speed throughout its subtests, improved reliability of causality can be inferred (Heaton, et al., 2001).

As the psychometric characteristics of the TEA-Ch have been reviewed it is next important to determine if this assessment measures the theorized multidimensional structure of attention. As the constructs of attention cannot be directly observed, factor analysis can be used as a statistical method to examine whether the associations among the observed variables can be accounted for by a smaller number of latent (unobservable) factors (Fruchter, 1954).

Statistical Analysis

Factor analysis is a method of data reduction with certain mathematical properties (Kim & Mueller, 1978). To understand the mathematics of factor analysis it is important to note that the observed variables or measured variables are "linear combinations of some underlying source variables" (Kim & Mueller, 1978, p. 8) also called factors. Researchers are often theoretically interested in these factors which can be labeled as either common or unique (Long, 1983). When the effects of factors are common to more than one of the observed variables, then they are called common factors (Long, 1983). Common factors are also known as latent factors or latent variables. When the effects of a factor are unique to only one observed variable they are called unique factors (Long, 1983). Unique factors are comprised of the variance that cannot be accounted for by the latent factor and may be attributed to the specific observed variable or to measurement error, or a combination of both. The overarching goal of factor analysis is to delineate a fewer number of latent factors through the relationships among the observed variables without losing the observed variables' information (Marcoulides & Hershberger, 1997). Thus, factor analysis is a method of data reduction. Two types of factor analysis are exploratory factor analysis and confirmatory factor analysis. Exploratory factor analysis primarily gives "insight(s) into the nature of abstract constructs" (Portney & Watkins, 2009, p. 706) and can be thought of as a means to build theory (Long, 1983). Confirmatory factor analysis on the other hand was developed as a way to test theory (Long, 1983). Therefore, exploratory factor analysis is considered a bottom-up approach and confirmatory factor analysis is frequently thought of as a top-down approach.

For a given theory, confirmatory factor analysis is used to test certain hypotheses regarding the number and relationship of specific common factor variables to the measured observed variables (Marcoulides & Hershberger, 1997). For example, a hypothesis could be postulated that there are two underlying dimensions or factors within a set of sample data and some variables belong to the first factor, whereas other variables belong to a second factor (Kim & Mueller, 1978). Through statistical analysis of the sample data, a proposed model can then be confirmed or not confirmed (Long, 1983). Confirmatory factor analysis is also considered a type of Structural Equation Model that uses measurement models to illustrate the associations between the observed measures and the latent factors (Brown, 2006).

Although attention was once thought of as a unitary construct, many researchers now support the multi-component nature of attention. In an effort to determine the best theoretical representation of an observed data structure, multiple models of attention can be tested through confirmatory factor analysis. For example, for a given set of observed variables a unitary one-factor model of attention can be initially tested. This one-factor model of attention can then be compared through goodness of fit indices derived from confirmatory factor analysis to a two-factor latent variable model of selective attention and sustained attention. Confirmatory factor analysis thus focuses on substantiating the unique underlying factor structure rather than ascertaining the factor(s) or latent variable(s) themselves (Marcoulides & Hershberger, 1997). This factor structure can then be visually depicted as a measurement model to indicate how the observed variables are linked to specific latent variables (Marcoulides & Hershberger, 1997).

Testing a Model of Attention using TEA-Ch Scores

Manly et al. (2001) conducted a confirmatory factor analysis on their normative TEA-Ch sample to determine if their data from the thirteen subtests of the TEA-Ch could be best explained by one general attention latent variable model or by a multidimensional, three latent variable model of selected, sustained, and control/switch attention. In the Manly et al. (2001) study, a measurement model was included to depict the factor loadings from the latent attention variables to the observed subtest variables as well as the latent attention factor intercorrelations. The unique variances of this prior study were not reported, however Manly et al. (2001) did include the Comparative Fit Index (CFI), the Normed Fit Index (NFI), and the Non-Normed Fit Index (NNFI) as their goodness of the fit indices.

The factor loadings for selective attention ranged from .55 to .79, attentional control/switch ranged from .51 to .77, and sustained attention ranged from .44 to .57. The intercorrelations were .72 for selective attention and attentional control/switch, .60 for attentional control/switch and sustained attention, and .40 for selective attention and sustained attention. The descriptive indices of the Manly et al. (2001) study demonstrated supportive values of CFI = .973, NFI = .913, and NNFI = .960 for their proposed three-factor model of attention.

When assessing the goodness of fit of a confirmatory factor analysis, descriptive indices should demonstrate values above .90 if the model is "well-fitting" (Marcoulides & Hershberger, 1997, p. 245). A chi-square goodness of fit measure comparison was also included in the Manly et al. (2001) study to determine if the acceptable fit of the threefactor model was attributed primarily to the performance of the older participants. Manly et al. (2001) thus, divided their sample into two groups around the median age of 10.91 years and determined that no significant differences were shown between the change in chi-square and change in degrees of freedom between the younger and older youth with $\chi^2(9) = 7.35$, p > .6. This comparison therefore supported the results of their confirmatory factor analysis of the three component nature of attention.

Conceptual Rationale for Using Raw Scores Controlling for Age and Gender

Age was found to have a significant effect on each of the nine subtest measures (Manly et al., 2001). Additionally, gender was found to have significant effects on Creature Counting and Sky Search subtests (Manly et al., 2001). Therefore, the raw scores for the nine subtest measures were transformed to normalized standard scores labeled age-scaled scores to remove the influence of age and gender (Manly et al., 2001). Age-scaled scores were used in the confirmatory factor analysis of the normative study. However, when standard scores are normalized to fit a normal distribution curve the actual value of the raw scores is not preserved (Davies & Gavin, 1999). Therefore, through "the normalization of the test data by the transformation to standard scores" (Manly et al., 2001, p. 1075) variability and preciseness of the data is lost. Consequently, use of raw scores with age and gender controlled might provide a better fit to this study's observed data.

PURPOSE

The overall purpose of this project was to determine if the TEA-Ch subtest measures reflect distinct aspects of attention based on data collected from a sample of American children age six to twelve years. Three questions regarding the American TEA-Ch data were addressed using a confirmatory factor analysis approach. The first question this project addressed was whether the three-factor model of attention that includes selective, sustained, and control/switch attention proposed by Manly et al. (2001) can be replicated using an American sample? The second question addressed was whether a four-factor model, including a divided attention factor, would provide a better fit to the observed data than a three-factor model? The third question this project addressed was whether the three-factor model can be improved through the use of raw scores and taking the effects of age and gender into account?

METHODS

TEA-Ch data from two prior studies funded by the National Institutes of Health (NIH) were used for the current study (Principal Investigator, Patricia L. Davies, PhD, R03 HD046512, "Reliability of Cognitive ERPs in Children and Adults" and Principal Investigator, Patricia L. Davies, PhD, R03 HD049532, "Sensory Gating Mediated by Attention." These previous studies will be briefly described. In Study A, a total of 92 participants were recruited; 32 adults and 60 typical children between the ages of 8.00 -12.90. In Study B, a total of 147 participants were recruited; 40 adults, 77 typical children between the ages of 5.00 - 11.92, and 30 children with symptoms of sensory processing dysfunction. Parents of the participants all gave informed consent and the participants gave assent. Children were recruited from the local northern Colorado community or through parent contact if a child had participated in past research projects conducted in this lab.

For both studies, participants attended two visits to the Brainwaves Research Laboratory at Colorado State University. The second visit occurred 1 to 2 weeks following the first visit on the same day of the week and time as the first visit to control for confounding factors in performance as these studies tested the reliability of brain processing. During the first visit, a researcher reviewed the demographic information sheet and consent forms with the parent and answered any questions that arose from the parent or child. In both studies, the children were involved in EEG testing for the first hour and behavioral testing for the second hour during each visit. All children were administered the TEA-Ch during one of the behavioral testing sessions. The Wechsler Abbreviated Scale of Intelligence (WASI), the d2 Test of Attention, and several other behavioral tasks were also given during a separate behavioral testing session.

An experienced researcher or research assistant administered the TEA-Ch in a quiet environment according to the manual's instructions. Auditory materials were presented through a portable laptop system with speakers. The tests were completed in the order set by the TEA-Ch manual. A research assistant then entered the subject's subtest assessment data from the TEA-Ch into an ACCESS computer database management system.

Participants

The participants of this study included 111 typically developing children, determined through parent questionnaire, between the ages of 6.0-12.9 years (M = 9.27, SD = 1.73). This study's analysis was completed using the TEA-Ch data from Study A and Study B. Participants were included if they met the inclusion criteria of age, between 6-12 years, and TEA-Ch assessment completion. Thus, 5-year-old participants in Study B were excluded due to age. Participants were also excluded from this study if a physical, neurological, or behavioral disorder was reported through a parent questionnaire. Children with sensory processing dysfunction were also excluded from this study. Having met these criteria, 56 children were included from study A and 55 children were included from study B.

Materials

Scores from the Test of Everyday Attention for Children (TEA-Ch), a standardized, normed assessment (Manly et al., 1999) were the primary data for this study. The nine subtests in the TEA-Ch align with the three systems of attention: sustained attention, selective attention, and attentional control/switching. The two dual task subtests are listed here under the category of sustained attention as suggested in the TEA-Ch manual. However, these two subtests were statistically examined to determine if a fourth factor of divided attention could be supported.

Selective attention. Sky Search. Participants are given a paired spacecraft search card and asked to circle the pairs of spacecraft that are the same as fast as possible. Children are then instructed to circle the correct pairs on another spacecraft search card with the distracters removed in order to control for possible motor speed differences. For both tasks, children mark a completion box to show that they are done and timing is stopped.

Map Mission. Participants are shown a city map and asked to circle all the knife and fork, restaurant symbols with various distracters present as fast as they can within one

minute. 80 targets are presented. The score given is the number of correct symbols circled within a minute.

Sustained attention. Score! Participants are required to silently count the number of tones heard without use of finger counting and then give the total. Two practice sessions are provided and then 10 test trials are given. Tones range in number from 9 to 15 for each trial.

Score Dual Task (DT). Participants count auditory tones silently and simultaneously listen out for the name of an animal within a news report. Two practice sessions are provided and then 10 trials are given. At the end of each trial, the child is asked to give both the number of tones and the name of the animal heard.

Code Transmission. Participants listen to an extended stream of numbers and are told to listen particularly for a double five sequence and then state the number said just prior. Practice is given and then 40 double five sequences are randomly said during this 12 minute task. Participants are asked to state the prior number to the double five sequence as it is heard in the moment.

Walk Don't Walk. Participants listen for a sound that is a "go" one-tone sound and mark one box within a 14 box vertical path on paper with a pen. However, children are instructed to refrain from marking a box when hearing the "no go" two-tone sound. Two demonstrations and two practice trials are first provided to ensure understanding and then the 20 test trials are given. Additionally, the rate between tones increases as the trials progress.

Sky Search Dual Task: Participants are asked to perform the subtests of Sky Search and Score! at the same time. This subtest requires the child to circle the spaceships that are the same while silently counting tones and then give the number of tones heard when the search is completed. A difference from Score! is that the tones for this subtest are presented consistently rather than randomly. Timing and/or accuracy are recorded for each task. Then the time per target score is divided by the proportion correct for the auditory counting to arrive at the Sky Search Dual Task score. The Sky Search score is then subtracted from the Sky Search Dual Task to measure the auditory demand of this subtest.

Attentional control/switching. Creature Counting. Participants are shown creatures in a tunnel with both upward and downward arrows randomly presented between the creatures. Children are asked to begin counting upward and continue counting upward if they see an upward arrow, but to start counting downward if they see a downward arrow. Two practice tasks are given followed by 7 test items. Both accuracy and speed are recorded.

Opposite Worlds. Participants are shown a weaving path of the numbers one and two. In the same world scenario children are asked to say the actual numbers one and two successively along the path as fast as they can. In the opposite world scenario children are asked to say two for the number one and one for the number two as they proceed along the path. Practice is provided for each scenario and then 4 test items are given. The time required for each test item is recorded.

Procedures

For this project the completion of TEA-Ch data entries from the two prior studies into the ACCESS database was verified. Research assistants assisted with data entry for age-scaled scores and checked for errors within the database. Conversion tables separated by gender and organized by age bands (6-7 years, 7-9 years, 9-11 years, 11-13 years, 13-15 years, and 15-16 years) found in the TEA-Ch manual were used to calculate each participant's age-scaled scores from their recorded raw scores. According to Manly et al. (2001) the age-scaled scores were scaled to a mean of 10 with a standard deviation of 3 and a range of 1 - 19. In the normative study, age-scaled scores were calculated through a multiple step statistical transformation process whereby the transformation "reflects the relationship of an individual's raw score to the mean and distribution of their age band" (Manly et al., 2001, p. 1074).

This data set of observed variables, age-scaled scores, was initially used to compute three correlation matrices. These correlation matrices were then entered separately into the LISREL 8 linear structural relations modeling system (Jöreskog & Sörbom, 1993). Using a confirmatory factor analysis approach, the three-factor

replication model, of selective, control/switch and sustained attention, using scaled scores was first examined. Next, as the zero-order correlations were higher for raw scores when compared to the zero-order correlations for scaled scores, a second threefactor model was explored by using raw scores while controlling for age. Raw scores were again used to test a third three-factor model controlling not only for age but also for gender to determine if the three-factor model could be improved. A four-factor model was then examined using scaled scores to determine if the inclusion of divided attention as a fourth latent variable in addition to selective, control/switch and sustained attention provided a better model fit. Lastly, a two-factor model using scaled scores was evaluated due to the high correlation coefficients between the latent factors in the three factor replication model.

Data Analysis

Manly et al. used age-scaled scores in their study; however, this project explored whether raw scores might provide a different or better account of the data as the variability and preciseness of the data is lost through the reduction in scale from ratio to interval when using age-scaled scores. Therefore, descriptive statistics were used to determine the normality of the distributions of the subtest measures of interest for both raw and standard scores. Pearson Product-Moment correlation coefficients were used to ascertain the relationship of the variables for both raw and scaled scores. SPSS version 19 was used to conduct the descriptive and correlation analyses.

Confirmatory factor analysis using the maximum likelihood algorithm of LISREL 8 (Jöreskog & Sörbom, 1993) was performed to investigate three three-factor, one fourfactor, and one two-factor model of attention for the nine subtests used in the Manly et al. (2001) study. When evaluating model fit all parameters should be examined including factor loadings, unique variances, factor intercorrelations, as well as goodness of fit indices. Multiple measures of goodness of fit of the proposed models' fit to the data should be used as several tests of significance and many descriptive indices of goodness of fit have been developed for confirmatory factor analysis (Marcoulides & Hershberger, 1997). No one goodness of fit index is considered more exemplary than another, as each index is sensitive to specific qualities of a data set (Bollen & Long, 1993). The chi-square goodness of fit, the Comparative Fit Index (CFI) (Bentler, 1990), the Normed Fit Index (NFI) (Bentler & Bonett, 1980), and the Non-Normed Fit Index (NNFI) (Bentler & Bonett, 1986) were the four goodness of fit indices included in the Manly et al. (2001) study. Therefore, we focused on these indices as well for comparison reasons.

The chi-square goodness of fit, test of significance, should be non-significant with p > .05 to conclude a good fit of the model to the data (Marcoulides & Hershberger, 1997). The descriptive indices of the CFI, NFI, and NNFI should demonstrate values above .90 if the model is "well-fitting" (Marcoulides & Hershberger, 1997, p. 245). Additional indices of fit were included in this study in order to incorporate indices from three fit categories: absolute fit, parsimony correction, and comparative or incremental fit (Brown, 2006). The standardized root mean square residual (SRMR) which reflects the average difference between the observed and predicted covariances (Brown, 2006) is provided in addition to the chi-square statistic as indices falling in the category of absolute fit. A SRMR of less than .08 is recommended to indicate a good fit of the model to the data (Brown, 2006). The root mean square error of approximation (RMSEA) evaluates how reasonably the model fits in the population (Brown, 2006) and is provided as an index in the parsimony category. The RMSEA is recommended to be close to or less than .06 (Brown, 2006). The CFI, NFI, and NNFI described earlier were included for comparison to the Manly et al. (2001) study and as members of the final category of comparative or incremental fit indices.

RESULTS

A summary of the primary descriptive statistics for the scaled scores of the nine subtest measures of the TEA-Ch is presented in Table 2. Thirteen raw score measurements were obtained for each child completing the TEA-Ch. However, only the nine subtest measurements as used in the confirmatory factor analysis by Manly and colleagues (2001) were computed for ease of replication. Non-normality of distribution of one subtest measure, Creature Counting, occurred in this study. Non-normality of distribution also occurred in the Manly et al. (2001) sample especially for Sky Search Dual Task with kurtosis = 50.54. The "imposition of cutoffs" (Manly et al., 2001, p. 1075) used for the Sky Search Dual Task subtest was given as an explanation of this leptokurtic value. Normality of distribution was met for the four age bands used in this study. Age band distribution of participants for this study and the Manly et al. (2001) normative study is shown in Table 3. Table 2.

Descriptive statistics for the standard score subtest measures of the TEA-Ch (N=111)

	Mean (SD)	Skewness	Kurtosis
Selective Attention			
Sky Search Time	9.52 (2.37)	004 (.229)***	.785 (.455)***
Map Mission	10.41 (2.90)	.443	.045
Control/Shift Attention			
Creature Counting	9.57 (2.46)	510*	1.088**
Opposite Worlds	8.56 (2.94)	115	.252
Sustained Attention			
Score!	9.79 (3.00)	098	803
Walk Don't Walk	6.56 (3.00)	.066	404
Code Transmission	7.86 (3.00)	163	036
Sky Search Dual Task	7.64 (3.63)	297	.121
Score Dual Task	10.29 (3.31)	002	215

NOTE * Normality violated. A *z* statistic was calculated by dividing the skewness statistic by the skewness standard error to determine if the skewness statistic was significantly difference than zero (which would represent a normal distribution.)

** Normality violated. A *z* statistic was calculated by dividing the kurtosis statistic by the kurtosis standard error to determine if the kurtosis statistic was significantly different than zero (which would represent a normal distribution.)

***The values in parentheses are the standard error of skewness and kurtosis respectively and are the same for each subsequent subtest.

Table 3.

Participant age band distribution for this study and the Manly et al. (2001) study sample.

Age Band	Brainwaves Research Lab	Manly et al. (2001)
6 to 6 years 11 months	10	38
7 to 8 years 11 months	44	56
9 to 10 years 11 months	37	54
11 to 12 years 11 months	20	58
13 to 14 years 11 months	0	59
15 to 15 years 11 months	0	29

The Replication Model

The first question asked in this study was could similar results from the

Australian normative study (Manly et al., 2001) be achieved using an American sample

that was condensed in a smaller age range? In other words, would there be a similar

distinction of the three processes of attention (i.e., selective, control shift, and sustained attention) using the data collected for this study. This question was addressed through a confirmatory factor analysis approach in replicating the measurement model established by Manly et al. (2001) for the TEA-Ch attention measure. A nine subtest item scaled score correlation matrix was calculated using SPSS version 19 and was subsequently analyzed by LISREL 8.51 (Jöreskog & Sörbom, 1993). This scaled score correlation matrix can be found in Appendix A.

The three-factor model with estimated factor loadings is shown in Figure 1. The completely standardized factor loadings are shown on the central straight single headed arrows pointing from the latent variables to the observed variables. The smaller numbers on the left with single-headed arrows pointing to the subtest variables are the unique variances for each subtest and the curved double-headed arrows to the right interconnecting the latent variables are correlation coefficients between the factors. Completely standardized solution factor loadings can be interpreted as standardized regression coefficients as the metrics of the observed variables and the latent factors are standardized (Brown, 2006).

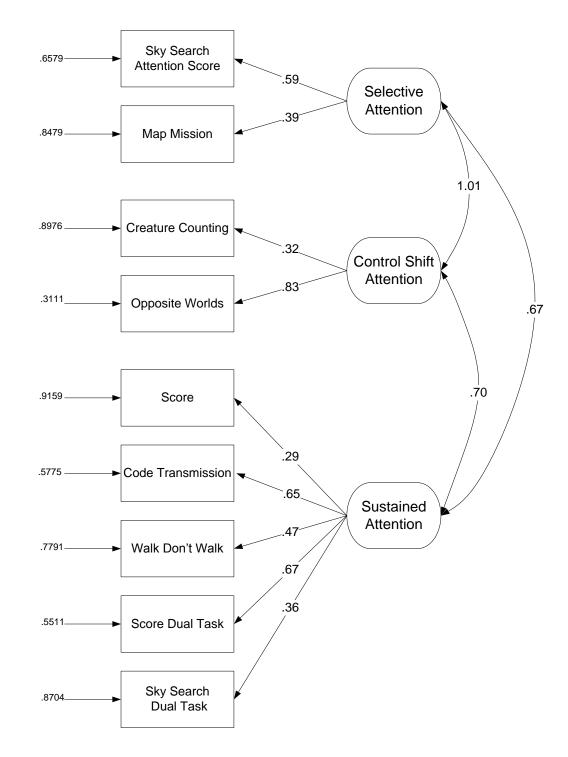


Figure 1. Measurement Model (Model 1) of TEA-Ch performance.

For the three-factor replication model, the observed variables, also known as indicator variables, were specified in the following manner. For selective attention, Sky Search and Map Mission were specified as indicator variables. For control shift attention, Creature Counting and Opposite Worlds were specified as indicators. Lastly, for sustained attention, the indicator variables were Score!, Code Transmission, Walk Don't Walk, Score Dual Task, and Sky Search Dual Task.

In order to perform a confirmatory factor analysis the "latent variable must have its scale identified" (Brown, 2006, p. 62). In order to do this, the researcher selects an observed variable as a marker indicator to represent the latent variable (Brown, 2006). Thus, one of the indicators is chosen to give a portion of its variance to the latent variable (Brown, 2006). Therefore, because of this process, a significance value cannot be calculated for the marker indicator. The values of the observed variables that were used to scale the latent variables (Sky Search for selective attention, Creature Counting for control shift attention, Score! for sustained attention, and Score Dual Task for divided attention) were set to 1.0 to establish a metric for the latent variables. Hence, the values for the variables were not freely estimated and their significance level can, by definition, not be determined. The same marker variables were used in all subsequent analyses.

The results of the confirmatory factor analysis for the three-factor replication model yielded estimated factor loadings for selective attention of .59 for Sky Search and .39 for Map Mission. Map Mission demonstrated significance, t = 3.29, p < .01. The

estimated factor loadings for control shift attention were .32 for Creature Counting and .83 for Opposite Worlds. Opposite Worlds demonstrated significance, t = 2.57, p < .02. Lastly, the estimated factor loadings for sustained attention were .29 for Score!, .65 for Code Transmission, .47 for Walk Don't Walk, .67 for Score Dual Task, and .36 for Sky Search. All factor loadings demonstrated significance for sustained attention; Code Transmission, t = 2.49, p < .02, Walk Don't Walk, t = 2.32, p < .02, Score DT, t = 2.50, p < .01, and Sky Search DT, t = 2.10, p < .02. The factor intercorrelations for the three factor model were 1.01 for selective attention and control shift attention, .70 for control shift attention and sustained attention, and .67 for selective attention and sustained attention and sustained attention.

The fit indices for the three-factor replication model are shown in the first row in Table 4. Specifically, the three-factor model provided a satisfactory fit to the data as it produced a nonsignificant chi-square, χ^2 (24, N = 111) = 34.63, *p* = .074, indicating that the estimated correlation matrix based on the model was not significantly different from the observed correlation matrix. In addition, the standardized root mean square residual (SRMR) of .069 was adequately below the suggested .08 level, and the root mean square error of approximation (RMSEA) of .063 was acceptable as being "close to" (Brown, 2006, p. 87) the suggested .06 or smaller point. The Comparative Fit Index (CFI) was .91, above the acceptable value of .90. Neither the Normed Fit Index (NFI) nor the Non-Normed Fit Index (NNFI) reached the acceptable level of .90 for the three factor model (see Table 4).

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Model	Df	χ^2	SRMR	RMSEA	NFI	NNFI	CFI
1. Three-factor	24	34.63,	.069	.063	.79	.86	.91
(scaled scores)		p = .074					
2. Four-factor	21	34.25,	.068	.076	.79	.81	.89
(scaled scores)		p = .034					
3. Two-factor	26	34.65 <i>,</i>	.069	.055	.79	.89	.92
(scaled scores)		p = .120					
4. One-factor	27	50.11	.079	.088	.71	.78	.84
(scaled scores)		p = .004					
5. Three-factor	24	46.90 <i>,</i>	.082	.092	.67	.68	.79
(raw scores*)		<i>p</i> = .003					
6. Three-factor	24	42.07,	.078	.083	.71	.75	.83
(raw scores**)		p = .013					

Fit indices for the three factor model and four plausible models.

*age removed

Table 4.

**age and gender removed

The Four-Factor Model

The second question in this study addressed was whether a four-factor model, including a divided attention factor, would provide a significantly better fit to the observed data than the three-factor model? For this second model the scaled score correlation matrix was again analyzed by LISREL 8.51 (Jöreskog & Sörbom, 1993) with parameters adjusted to delineate the new hypothesized fourth latent variable. The fourfactor model with estimated factor loadings is shown in Figure 2.

For the four-factor model, the indicator variables were specified in the following manner. For selective attention, Sky Search and Map Mission were specified as indicator variables. For control shift attention, Creature Counting and Opposite Worlds were specified as indicators. For sustained attention, the indicator variables were Score!, Code Transmission, and Walk Don't Walk. Lastly, for divided attention Score Dual Task and Sky Search Dual Task were specified as indicators.

The results of the confirmatory factor analysis for the four-factor model yielded estimated factor loadings for selective attention of .59 for Sky Search and .39 for Map Mission. Map Mission demonstrated significance, t = 3.30, p < .01. The estimated factor loadings for control shift attention were .32 for Creature Counting and .83 for Opposite Worlds. Opposite Worlds demonstrated significance, t = 2.58, p < .02. The estimated factor loadings for sustained attention are .28 for Score!, .67 for Code Transmission, and .49 for Walk Don't Walk. Both factor loadings for sustained attention demonstrated significance; Code Transmission. t = 2.35, p < .05 and Walk Don't Walk, t = 2.22, p < .05. Lastly, the estimated factor loadings for divided attention were .67 for Score Dual Task and .36 for Sky Search Dual Task. Sky Search Dual Task demonstrated significance, t = 2.84, p < .01. The factor intercorrelations for the four-factor model were 1.01 for selective attention and control shift attention, .68 for control shift attention and sustained attention, .69 for selective attention and sustained attention, .70 for control shift attention and divided attention, .93 for sustained attention and divided attention, and .63 for selective attention and divided attention.

Although there were noted similarities between the first model and the second model, the first model remained the strongest. For the second model, the test statistic χ^2 was significant, χ^2 (21, N = 111) = 34.25, *p* = .034. The SRMR was .068 and the RMSEA was .076. The goodness of fit indices did not reach .90 with NFI = .79, NNFI = .81,

and CFI = .89. The noted similarities in performance of the second model and the first model were found in the values of the SRMR statistic and the NFI. The SRMR of the first model was .069 and the SRMR of the second model was .068, both below the recommendation of .08. Also, the NFI for both the first model and the second model were the same at .79. However, the test statistic χ^2 and the RMSEA for the second model did not meet criteria for acceptable model fit. The second model NNFI of .81 was lower than the NNFI of .89 of the first model and the second model CFI of .89 was lower than the CFI of .92 of the first model. Additionally, when evaluating the change in the χ^2 test statistic and degrees of freedom between the first model and the second model, a significant improvement in model fit was not observed.

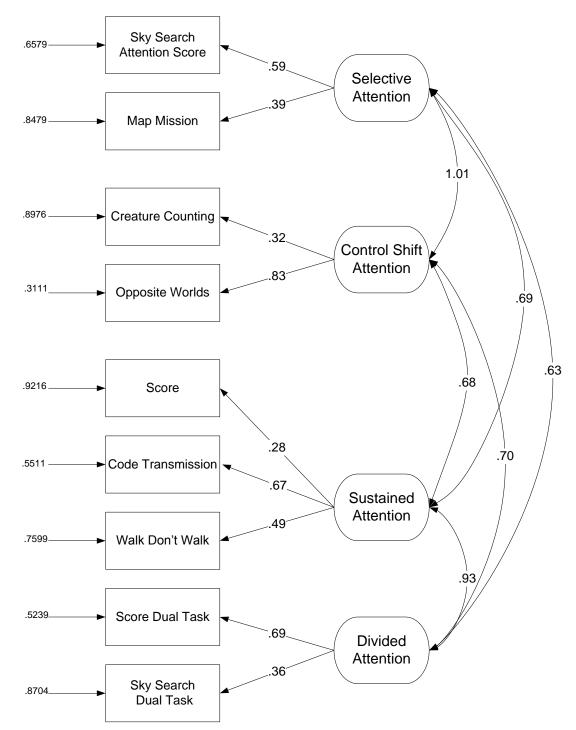


Figure 2. Measurement Model (Model 4) of TEA-Ch performance.

The Two-Factor Model

To this point, the three-factor model using scaled scores yielded the best explanation of the data when evaluating the two models formulated. However, when examining the latent factor intercorrelations of the three-factor and four-factor factor models, an out of range association result of 1.01 between selective attention and control shift attention in both models indicated that these models may be misspecified. Therefore, a third two-factor model consisting of visual control attention and sustained attention was analyzed. The two-factor model with estimated factor loadings is shown in Figure 3.

For the two-factor model, the indicator variables were specified in the following manner. For the combined selective attention and control shift attention factor now labeled as visual control attention, Sky Search, Map Mission, Creature Counting, and Opposite Worlds were specified as indicators. For sustained attention, the indicator variables were Score!, Code Transmission, Walk Don't Walk, Score Dual Task, and Sky Search Dual Task.

The results of the confirmatory factor analysis for the two-factor model yielded estimated factor loadings for visual control attention of .58 for Sky Search, .39 for Map Mission, .32 for Creature Counting, and .84 for Opposite Worlds. All factor loadings for visual control attention demonstrated significance; Map Mission, t = 3.31, p < .01, Creature Counting, t = 2.78, p < .01, and Opposite Worlds, t = 4.64, p < .001. The estimated factor loadings for sustained attention were .29 for Score!, .65 for Code Transmission, .47 for Walk Don't Walk, .67 for Score Dual Task, and .36 for Sky Search. All factor loadings for sustained attention demonstrated significance; Code Transmission, t = 2.50, p < .02, Walk Don't Walk, t = 2.32, p < .05, Score Dual Task, t = 2.51, p < .01, and Sky Search Dual Task, t = 2.10, p < .05. The latent factor intercorrelation for the two-factor model was .68 for visual control attention and sustained attention.

For this model the χ^2 test statistic was nonsignificant demonstrating an acceptable fit to the data at χ^2 (26, N = 111) = 34.65, *p* = .120 The SRMR was acceptable at .069 and the RMSEA was also acceptable at .055. The goodness of fit indices were NFI = .79, NNFI = .89, and the CFI = .92. In comparing the two-factor model to the three-factor model using scaled scores, the SRMR of both models was equal at .069; however, the RMSEA of .055 of this third model demonstrated improvement from the first model's RMSEA of .063. Improvement of two goodness of fit indices was also observed for the two-factor model. The NNFI was higher at .89 for the two-factor model when compared to the NNFI of .86 for the three-factor model. The CFI was also higher for the two factor model at .92 when compared to the CFI of the three factor model of .91. The NFI for both models was equal at .79. When evaluating the change in the χ^2 test statistic and degrees of freedom between the three-factor model and two-factor model using age-scaled scores, a significant improvement in model fit was not observed. However, as this two-factor model provided an acceptable model fit as well as an improved model fit

across several goodness of fit indices, the two-factor model is favored and considered conceptually more parsimonious.

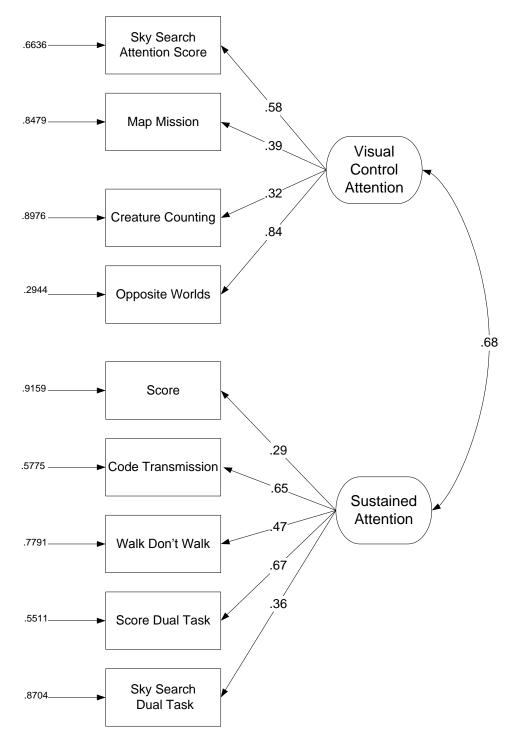


Figure 3. Measurement Model (Model 5) of TEA-Ch performance.

One-Factor Model

Due to the high intercorrelation (.68) between the visual control attention factor and the sustained attention factor a one-factor structural model of attention was also examined. The Sky Search selective attention subtest was labeled as the marker indicator and all other subtests were designated as indicators of the sole latent factor of attention.

The results of the confirmatory factor analysis for the one-factor model provided the following estimated factor loadings for the unified attention factor: .55 for Sky Search, .37 for Map Mission, .32 for Creature Counting, .72 for Opposite Worlds, .22 for Score!, .59 for Code Transmission, .45 for Walk Don't Walk, .62 for Score DT, and .27 for Sky Search DT. With the exception of Score!, t = 1.95, p < .10, all factor loadings were significant; Map Mission, t = 3.05, p < .01, Creature Counting, t = 2.68, p < .02, Opposite Worlds, t = 4.70, p < .001, Code Transmission, t = 4.27, p < .001, Walk Don't Walk, t =3.55, p < .01, Score Dual Task, t = 4.39, p < .001, and Sky Search Dual Task, t = 2.30, p <.05. Regarding the descriptive indices for the one-factor model, the χ^2 test statistic was significant demonstrating an unacceptable fit to the data at χ^2 (27, N = 111) = 50.11, p =.004. The SRMR of .079 was acceptable as less than .08, but the RMSEA of .088 was above the recommendation of .06. The comparative fit indices were NFI = .71, NNFI = .78, and the CFI = .84.

In comparing the one-factor model to the two-factor model, minimal changes in factor loadings occurred. However, the chi-square test statistic was significant and the

RMSEA was above the .06 recommendation demonstrating a poor fit of the one-factor model to the data. The SRMR was lower and thus more desirable for the two-factor model at .069 in comparison to the one-factor model SRMR of .079. Additionally, the comparative fit indices were all higher for the two-factor model, NFI = .79, NNFI = .89, CFI = .92, when evaluated next to the one-factor model, NFI = .71, NNFI = .78, CFI = .84. Thus, the two-factor model remained the most favorable model of the factor structures examined.

Three-Factor Models with Raw Scores

The third question raised in this study was could the three-factor model of attention be improved by using raw scores while controlling for age and gender. Specifically, would use of raw scores for the observed variables account for more variance in the data indicating that possibly information was lost by using scaled scores? Using confirmatory factory analysis this question was addressed through direct statistical comparison of the two raw score alternative models with the three-factor model which used scaled scores. The correlation matrix using raw scores with age controlled can be found in Appendix B.

For the three-factor raw score model controlling for age, the indicator variables were specified in the following manner. For selective attention, Sky Search and Map Mission were specified as indicator variables. For control shift attention, Creature Counting and Opposite Worlds were specified as indicators. Lastly, for sustained

attention, the indicator variables were Score!, Code Transmission, Walk Don't Walk, Score Dual Task, and Sky Search Dual Task.

The results of the confirmatory factor analysis for the three-factor raw score model with age controlled yielded estimated factor loadings for selective attention of .35 for Sky Search and -.19 for Map Mission. Map Mission did not achieve significance, *t* = -.86, *p* > .20. The estimated factor loadings for control shift attention were .16 for Creature Counting and 1.12 for Opposite Worlds. Opposite Worlds did not achieve significance, *t* = .80, *p* > .20. Lastly, the estimated factor loadings for sustained attention were .50 for Score!, .43 for Code Transmission, .34 for Walk Don't Walk, .70 for Score Dual Task, and -.51 for Sky Search Dual Task. All factor loadings for sustained attention demonstrated significance; Code Transmission, *t* = 3.11, *p* < .01, Walk Don't Walk, *t* = 2.58, *p* < .02, Score Dual Task, *t* = 3.82, *p* < .001, and Sky Search Dual Task, *t* = -3.44, *p* < .01. The factor intercorrelations for the three-factor raw score model with age controlled were .93 for selective attention and control shift attention, -.43 for control shift attention and sustained attention, and -.54 for selective attention and sustained attention.

In this fifth model, the indices of fit were all less desirable than the first model. The test statistic χ^2 demonstrated significance, $\chi^2(24, N = 111) = 46.90, p = .003$ indicating that the estimated correlation matrix based on the model was significantly different from the observed correlation matrix. The SRMR of .082 was higher than the recommended .08 level and the RMSEA at .092 likewise was higher than the recommendation of .06 or lower. Additionally, none of the goodness of fit indices reached the .90 acceptable level of model fit.

For the sixth model, the use of raw scores with age and gender controlled of the nine subtest measures was analyzed. The correlation matrix for this model can be found in Appendix C.

For the three-factor raw score model controlling for age and gender, the indicator variables were specified in the same manner as the fourth model. For selective attention, Sky Search and Map Mission were specified as indicator variables. For control shift attention, Creature Counting and Opposite Worlds were specified as indicators. Lastly, for sustained attention, the indicator variables were Score!, Code Transmission, Walk Don't Walk, Score Dual Task, and Sky Search Dual Task.

The results of the confirmatory factor analysis for the three-factor raw score model with age and gender controlled yielded estimated factor loadings for selective attention of .35 for Sky Search and -.18 for Map Mission. Map Mission did not achieve significance, t = -1.84, p > .05. The estimated factor loadings for control shift attention were .16 for Creature Counting and 1.09 for Opposite Worlds. Opposite Worlds did not achieve significance, t = .85, p > .20. Lastly, the estimated factor loadings for sustained attention were .51 for Score!, .43 for Code Transmission, .32 for Walk Don't Walk, .71 for Score Dual Task, and -.54 for Sky Search Dual Task. All factor loadings for sustained attention demonstrated significance, Code Transmission, t = 3.17, p < .01, Walk Don't Walk, t = 2.52, p < .02, Score Dual Task, t = 3.96, p < .001, Sky Search Dual Task, t = -3.62, p < .01. The factor intercorrelations for the three-factor raw score model with age and gender controlled were 1.0 for selective attention and control shift attention, -.45 for control shift attention and sustained attention, and -.55 for selective attention and sustained attention.

For this sixth model, the test statistic χ^2 demonstrated significance, χ^2 (24, N = 111) = 42.07, *p* = .013. The value of SRMR was .078 and the RMSEA statistic was .083. Additionally, none of the goodness of fit indices reached the .90 level (NFI = .71, NNFI = .75, and CFI = .83.) Although the SRMR of .078 was slightly below the recommendation of .08, Model 1, which used scaled scores, had a lower SRMR value of .069. The RMSEA for this model was above the recommended level of .06 and all goodness of fit indices although higher than the second model, remained lower than the original model.

Factor Loading and Correlation Comparison

The completely standardized factor loadings of the first model were significant and ranged from .29 to .83 and are shown as the straight single headed arrows pointing from the latent factors to the subtest variables in Figure 1. The factor loadings of the second model were also all significant and similarly ranged from .28 to .83 and are shown in Figure 2. The factor loadings of the third model were likewise all significant and ranged from .29 to .84 and are shown in Figure 3. Differing from these three models, the factor loadings of the fourth model ranged from -.51 to 1.12 with the selective attention and control shift attention latent variables demonstrating nonsignificance whereas the sustained attention factor loadings achieved significance.

Similar to the fourth model, the fifth model factor loadings were nonsignificant for the selective attention and control shift attention factor loadings and significant for the sustained attention factor loadings. The factor loading range for the fifth model was -.54 to 1.09. As models four and five achieved factor loadings that were negative as well as greater than one in value, known as "Heywood cases" (Brown, 2006, p. 74), these two models appear to be improper solutions. When comparing the factor loadings of the three-factor replication model of this study with the factor loadings reported by Manly et al. (2001), higher factor loadings were noted with five subtest measures and lower factor loadings were observed for four subtest measures shown in Table 5.

The correlation coefficients of the three-factor replication model between the latent factors for the selective and control shift factors of 1.01, the control shift and sustained factors of .70, and the selective and sustained factors of .67 indicate a strong association between the factors and suggest a unity of the attentional processes. Interestingly, the correlations coefficients between the latent factors in this present study were higher than those derived in the normative study. Results of the Manly et al. (2001) study reported correlation coefficients of .72 for selective and control shift, .60 for control shift and sustained, and .40 for selective and sustained factors. Table 5.

	Selective	Control Shift	Sustained
Sky Search Attention Score	.59 (.55) *		
Map Mission	.39 (.79)		
	p < .01		
Creature Counting Timing		.32 (.51)	
		*	
Opposite Worlds		.83 (.77)	
		р < .02	
Score!			.29 (.52)
			*
Code Transmission			.65 (.49)
			<i>p</i> < .02
Walk Don't Walk			.47 (.46)
			<i>p</i> < .02
Score Dual Task			.67 (.57)
			p < .01
Sky Search Dual Task			.36 (.44)
			<i>p</i> < .02

Completely standardized solutions of factor loadings. Manly et al. (2001) are shown in parentheses.

*designates a marker indicator for which significance cannot be calculated. *p*-values given are representative of the factor loadings of this study.

DISCUSSION

This study sought to determine if the TEA-Ch data sample would reveal distinct aspects of attention, namely selective, control shift, and sustained attention. The primary objective of this study was to examine if a similar measurement model fit achieved from the large Australian normative sample (Manly et al., 2001) could be replicated with a smaller, more restricted age range sample collected in the United States using a confirmatory factor analysis approach. The second main objective was to determine if the addition of divided attention as a fourth distinct process of attention might better explain the data from this sample.

Regarding the primary objective, results of the replication confirmatory factor analysis of the three-factor model of attention demonstrated similarities with the Manly et al. (2001) sample in factor loadings for Sky Search Attention and Walk Don't Walk, selective and sustained measures respectively. Additionally, sustained attention demonstrated higher factor loadings for Code Transmission and Score DT in comparison to the Manly et al. (2001) sample. Also, selective attention demonstrated smaller factor loadings for Map Mission, control shift attention demonstrated smaller factor loadings for Creature Counting, and sustained attention demonstrated smaller factor loadings for Sky Search DT than the Manly et al. (2001) sample. In thinking about these differences in factor loadings one possible explanation arises. This study's younger population might explain these differences in factor loadings as several of this assessment's subtests require executive function skills. Attentional performance has been shown to be developmental in nature and overlaps with the executive function skills of working memory, attentional shift, and inhibition. As children progress through their early school years, attentional abilities and executive function abilities increase systematically with age. Thus, the demands placed on children in school also increases as they are able to perform more complex tasks. For example, the smaller factor loading of control shift attention for the Creature Counting subtest may be attributed to the limited working memory of numeracy knowledge of younger participants.

In comparing the goodness of fit indices between this study's sample and the Manly et al. (2001) sample, confirmatory factor analysis results indicated that the three indices reported by Manly et al. (2001) were stronger (CFI = .973, NFI = .913, and NNFI = .960) in comparison to this study's results (CFI = .91, NFI = .79, and NNFI = .86.) The statistically non-significant p value of the chi-square goodness of fit index also was larger χ^2 (24) = 33.43, p = .10 (Manly et al. 2001) in comparison to this study, χ^2 (24, N = 111) = 34.63, p = .074. However, both models support the null hypothesis that the model approximations adequately reproduced the sample covariance structure.

With respect to the replication model's correlations among factors, the present study's sample produced larger correlation coefficients than the Manly et al. (2001) sample which may indicate that the attentional processes of younger children may not be developmentally as differentiated yet. In investigating the possibility that attention is a unitary construct, Manly et al. (2001) tested the model fit of a single latent variable. Following confirmatory factor analysis, Manly et al. (2001) determined that the threelatent factor model of selective, control shift, and sustained attention performed superior to a unitary model of attention. However, the larger associations between the factors found in this study's replication model suggest that selective and control shift attention, as represented in this assessment, may not be distinct constructs of attention for younger children. One possible explanation could be that the selective attention visual search tasks as found in Sky Search and Map Mission may require inhibition in addition to target detection which may be more difficult for younger children and more automatic for older children.

The authors of the TEA-Ch, Manly et al. (1999), reported that the first four subtests administered in this assessment may be used as a screening tool and include Sky Search, Score!, Creature Counting, and Sky Search DT. It is not clear in the TEA-Ch manual (Manly et al., 1999) why these four subtests were selected other than each represents a construct of attention: selective, control shift, sustained, and divided attention. Factor loadings could be used as guidance to suggest which of the subtests best represent each construct of attention. However, when looking at the factor

loadings of the measurement model of the Manly et al. (2001) study only the Score! subtest measure had a relatively high factor loading on sustained attention (.52). In the normative sample, Map Mission (.70) had a higher factor loading on selective attention than Sky Search (.55). Opposite Worlds (.77) achieved a higher factor loading on control shift attention than Creature Counting (.51). Lastly, Score DT (.57) had a higher factor loading than Sky Search DT (.44).

In addition, "completely standardized factor loadings can be interpreted as the correlation of the indicator with the latent factor" (Brown, 2006, p. 133). Thus, the measurement model analysis in this present study illustrated that selective attention associated more with Sky Search Attention (34.8%) than with Map Mission (15.2%). Control shift attention associated more with Opposite Worlds (86.9%) than with Creature Counting (10.2%); and sustained attention associated more with Code Transmission (42.3%) and Score DT (44.9%), than with Score! (8.4%), Walk Don't Walk (22.1%), and Sky Search DT (13.0%).

Based on the results of the replication three-factor model measurement model for this sample the combination of Sky Search, Opposite Worlds, Code Transmission, and Score DT used as a screening tool may better represent the constructs of selective, control shift, and sustained attention. However, when examining the normative sample's factor loadings the combination of Map Mission, Opposite Worlds, Score!, and Score DT is supported as representative of the constructs of selective, control shift, and

sustained attention. Therefore, although Opposite Worlds and Score DT are commonalities between these two samples, further research regarding the best combination of subtest item inclusion in the screening tool appears necessary.

With respect to the screening tool, it is interesting that the highest factor loadings of the subtest measures for the replication three-factor model and the more parsimonious two-factor model were the same. A difference occurred only in regards to the model structure. Selective attention and control shift attention each had one subtest indicator and sustained attention had four subtest indicators for the threefactor model, whereas the two-factor model had three subtest indicators for the visual control attention factor and four subtest indicators for the sustained attention factor. **Models Using Raw Scores**

The data of the three-factor model were further investigated to determine if use of raw scores rather than scaled scores would explain more of the variance in this sample's data as the zero-order correlations were higher for raw scores versus scaled scores. When data is reduced from ratio-level raw scores to interval-level standard scores (age-scaled scores) some specificity of the data may be lost (Portney & Watkins, 2009). Additionally, through transformations designed to normalize data, as used in the creation of the age-scaled scores, decreased variability occurs. Therefore, two separate bivariate correlation matrices using the raw score data and controlling for age and then age and gender were calculated and examined by LISREL 8.51 (Jöreskog & Sörbom,

1993). Loss of goodness of fit was noted with both of these models in comparison to the original three-factor model.

Raw scores were used in two of the proposed models to determine if the information lost when converting raw scores to standardized age-scaled scores would account for more variance and yield a better explanation of these American data to the components of attention. However, it appears that the use of interval level scaled scores may be more representative of the constructs of attention and furthermore supports an ordered developmental nature of attention. Also, improved model fit when using scaled scores may have occurred as scaled scores guard against psychometric properties such as ceiling affects and test item order (Manly et al., 2001). Lastly, the violation of the multi-normality assumption suggest that the Maximum Likelihood estimation procedure of LISREL is not the appropriate algorithm to use and if used will lead to improper solutions. Instead, a robust Maximum Likelihood estimator, such as PRELIS, should be used as it tests for normality and generates a covariance matrix and asymptotic covariance matrix for use as input in the confirmatory factor analysis run by LISREL (Brown, 2006).

In addressing the second main objective, the original three-factor model performed superior to the four-factor model with the addition of divided attention as a latent factor with respect to the comparison between goodness of fit indices. However, when evaluating the change in the χ^2 test statistic and degrees of freedom between the three-factor model and the four-factor model, a significant difference in model fit was

not observed. Although RMSEA and SRMR were not included in the Manly et al. (2001) study, they were included in this study due to their "satisfactory performance" in simulations (Brown, 2006, p.86). Additionally, although goodness of fit indices offer evaluation of model fit, demonstrating the improved fit of one model among other thoughtfully planned models is often desirable and recommended (Thompson, 2000). Overall, the absolute fit, parsimony correction, and comparative fit indices were more favorable for the three-factor model hypothesized by Manly et al. (2001). Thus, the two divided attention tasks fit better within the construct of sustained attention versus divided attention as these dual task measures appear to have stronger association with the prolonged auditory performance demands of the sustained attention subtest measures.

Two-Factor Model

An additional question arose during the data analyses of this study. Due to the large correlation coefficient between selective attention and control shift attention in the three-factor model, a two-factor model structure of visual control attention and sustained attention was examined. For the two-factor model an acceptable fit to the data was shown and several indices of fit demonstrated improvement when compared to the replication model. With its acceptable fit to the data and smaller latent variable structure, the two-factor model was considered conceptually more parsimonious in comparison to all models presented. However, when evaluating the change in the χ^2 test statistic and degrees of freedom between the three-factor and the two-factor models, a

significant improvement in model fit was not observed. Thus, although this study's data suggest that there may be an overlapping of the attentional processes of selective attention and control shift attention that is specific to this study's younger sample these results should be interpreted cautiously as the model fit of the three-factor, four-factor, and two-factor structures is not significantly different.

Manly et al. (2001) reported performing further analyses comparing a younger grouping to an older grouping within their normative sample to determine if the results of their measurement model occurred primarily due to the older participants. Associations between the subtest scores and the latent variables were reported as not significantly different (Manly et al., 2001). Had the correlation matrix of this younger sample been provided, similarities and differences regarding factor loadings, factor intercorrelations, and goodness of fit indices could have been investigated with regard to the younger normative sample and this study's sample. Further research with both younger and older samples is thus recommended to ascertain the attentional processing differences between these two populations.

Limitations

Similar to most studies, this study had several limitations. As this study was a secondary analysis of data previously collected, only children ages 6 to 12 years were included. Thus, the children for this study were in a younger and more restricted age range than the Manly, et al. (2001) study. As a result, this study's sample includes representation from four of the six age bands; 6- year olds, 7-year olds to 8-year olds, 9-

year olds to 10-year olds, and 11- year olds to 12- year olds. The age bands lacking representation in this sample were 13-year olds to 14-year olds and 15-year olds.

A second limitation of this study was that normality of distribution was not met for one subtest, Creature Counting. This subtest achieved skewness and kurtosis *z* values above the absolute value of 1.96. A *z* value was calculated by dividing the skewness statistic by the skewness standard error to determine if the skewness statistic was significantly difference than zero (which would represent a normal distribution.) This calculation was likewise performed with the kurtosis statistic and kurtosis standard error. Confirmatory factor analysis conducted using maximum likelihood estimation assumes adequate sample size, interval scale data, and multivariate normality (Brown, 2006). However, research has demonstrated that maximum likelihood estimation is "robust to non-normality" (Brown, 2006, p. 379).

A third limitation of this study was its smaller sample size. Although a larger sample would have been advantageous for comparison to the normative sample, Bentler and Chou (1987) have recommended a ratio of sample size to estimated parameters of between 5 and 10. In this current study, the sample size to parameter ratio was met at 6.17 for the three-factor replication model and 6.94 for the two-factor model, yet both n/k ratios were near the lower end of this range. Thus, a larger sample size would have been more ideal.

Conclusion

In summary, this study replicated the three-factor structure of the nine subtests of the TEA-Ch using secondary data. Although the three-factor replication model achieved several acceptable measures of goodness of fit, a two-factor model structure combining selective attention and control shift attention into a visual control attention factor along with sustained attention provided the best explanation of this study's data. Additionally, evidence of divided attention as a fourth latent factor for this sample was not supported through confirmatory factor analysis.

As the incidence of children diagnosed with Autism Spectrum Disorders and ADHD continues to grow, the need for objective measures of attentional performance is clearly warranted for evaluating attentional differences and guiding promising interventions such as computerized attention training (Rueda, Posner, & Rothbart, 2005). As attentional differences may be distinct among neurodevelopmental disabilities, the TEA-Ch is a valuable tool for practitioners and researchers as it provides a valid assessment of different aspects of attention. One possible drawback of the TEA-Ch is the hour required for children to complete its nine subtests. A briefer screening tool of the first four subtests of the TEA-Ch is suggested when time constraints arise. However, further analysis is recommended to determine if the four subtests in the TEA-Ch screening tool are optimal. Thus, further research is needed with respect to shorter multidimensional assessments of attention to inform intervention and consequently improve the quality of life for persons with attentional differences.

			APPENDIX A	DIXA					
Pearson Correlation Co	Coefficients for the Scaled Scores of the Nine Subtest Measures (N = 111)	s for the	Scaled S	cores of	the Nin€	e Subtest	Measur	es (N = 1	11)
	1	2	3	4	5	9	7	8	6
1. Sky Search Attention	H								
2. Map Mission	.229*	1							
3. Creature Counting	.194*	0.065	1						
4. Opposite Worlds	.492**	.330**	.264**	1					
5. Score!	0.017	0.16	-0.106	0.104	1				
6. Code Transmission	.255**	0.157	.232*	.381**	0.154	1			
7. Walk Don't Walk	.244**	0.176	0.079	.271**	-0.06	.388**	1		
8. Score Dual Task	.303**	0.164	0.163	433**	.343**	.368**	.286**	Ч	
9. Sky Search Dual Task	-0.013	0.077	0.142	0.08	.235*	.306**	0.146	.247**	-
<i>p</i> < .05.									
** <i>p</i> < .01.									

			APPEN	APPENDIX B					
Pearson Correlation Coeff	ficients fo	r the Raw	Scores A	ge Contro	lled of th	e Nine Su	btest Me	fficients for the Raw Scores Age Controlled of the Nine Subtest Measures (N = 111)	= 111)
	1	2	c	4	5	9	7	8	6
1. Sky Search Attention	1								
2. Map Mission	-0.066	1							
3. Creature Counting	0.053	0.064	1						
4. Opposite Worlds	.366**	189*	0.18	1					
5. Score!	-0.037	0.136	0.067	-0.11	1				
6. Code Transmission	-0.095	0.122	-0.145	238*	0.175	1			
7. Walk Don't Walk	-0.183	.191*	-0.062	259**	-0.024	.391**	1		
8. Score Dual Task	-0.13	0.024	-0.069	413**	.402**	.228*	.201*	1	
9. Sky Search Dual Task	-0.022	-0.145	0.128	0.166	418**	252**	-0.143	316**	1
* <i>p</i> < .05									
**p < .01									

			AF	APPENDIX C					
Pearson Correlation Coefficients for the Raw Scores Age and Gender Controlled of the Nine Subtest Measures (N = 111)	efficients fo	or the Raw	Scores Age	and Gende	er Controll€	ed of the Ni	ine Subtest	: Measures	(N = 111)
	1	2	3	4	5	6	7	8	6
1. Sky Search Attention	1								
2. Map Mission	-0.062	1							
3. Creature Counting	0.058	0.065	1						
4. Opposite Worlds	.385**	-0.187	0.175	1					
5. Score!	-0.025	0.136	0.058	-0.125	1				
6. Code Transmission	-0.125	0.13	-0.146	228*	.200*	1			
7. Walk Don't Walk	206*	.201*	-0.05	234*	-0.01	.374**	1		
8. Score Dual Task	-0.14	0.016	-0.066	426**	.400**	.236*	0.185	1	
9. Sky Search Dual Task	-0.015	-0.137	0.136	.195*	400**	263*	-0.153	349**	1
* <i>p</i> < .05									
** <i>p</i> < .01									

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