EXPLORATORY AND CONFIRMATORY FACTOR ANALYSIS OF THE ABERRANT BEHAVIOR CHECKLIST-COMMUNITY IN AN AUTISM SPECTRUM DISORDER SAMPLE WITH RATNGS COMPLETED BY SPECIAL EDUCATION STAFF

By

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ABSTRACT

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Although there are established measures to diagnose Autism Spectrum Disorder (ASD), there are no currently comparable measurement tools available to assess outcomes for core and associated features for ASD interventions. One scale, the Aberrant Behavior Checklist-Community (ABC-C; Aman & Singh, 2017), originally developed to assess intervention research outcomes for problematic behavior and associated features in individuals with intellectual disability (ID), appears to be a promising option for this purpose. The 58-item ABC-C rating scale has become a popular choice amongst ASD intervention researchers (Bolte & Diehl, 2013). Many of the core and associated features of ASD, the prime targets of intervention, are represented within the scale. However, ABC-C validity research in the ASD population specifically is still limited. Previously, three exploratory factor analyses (EFA; Brinkley et al., 2007; Kaat, Lecavalier, & Aman, 2014; Mirwis, 2011) and two confirmatory factor analyses (CFA; Brinkley et al., 2007; Kaat et al., 2014) have been performed on the ABC-C in ASD samples. These analyses have yielded inconsistent factor solutions across studies, with marginally fitting models upon testing. This has left questions about the rigor or thoroughness of the analytic strategies, including the range of factor solutions examined, the logic behind the selection of the factor solutions retained, and possible differences due to rater type. Thus, additional thorough and independent factor analyses were warranted for the purpose of determining whether the ABC-C authors' posited five-subscale interpretive structure is the most

appropriate, useful, and valid for the ASD population or if an alternative model is more suitable. Present study one involved using EFA to examine the data structure of the ABC-C in an ASD sample (N = 300), age range 3.17 to 21.05 years, based on ratings provided by special education staff. A nine-factor solution was retained following examination of factor models consisting of between three and 11 factors. Study two involved using CFA to test the absolute and relative fit of the derived ABC-C factor solution from the EFA of study one with an ASD validation sample (N = 243), age range 2.95 to 21.15 years, across five fit indices (Chi Square [χ^2], Standard Root Mean Square Residual [SRMR], Root Mean Square Error of Estimation [RMSEA], Comparative Fit Index [CFI], and the Tucker-Lewis Index [TLI]). The fit of the factor model from study one was then directly compared to the fit of the existing models of the ABC-C found in ASD samples (or proposed for use with individuals with ASD) using Akaike's Information Criterion (AIC) and the Bayes Information Criterion (BIC). Results from the CFA revealed the nine-factor model from study one meeting or approximating cut off-values on the SRMR, RMSEA, CFI, and TLI. Results from the AIC and BIC fit tests showed the nine-factor model to be the best fitting model compared to the other existing models of the ABC-C found in ASD samples. Findings from study one and two highlight the possibility that the current five-factor author version of the ABC-C is potentially not the most viable model for the ASD population and the nine-factor version may be a more appropriate choice. Findings also underscored the need for similarly rigorous factor analytic methodology to be employed in future replication studies, and the recommendation for a major scale revision of the ABC-C.

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For my wife, Amy.
For my parents, Mel and Joan.

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CHAPTER 1: INTRODUCTION

Autism Spectrum Disorder (ASD) is classified as a neurodevelopmental disorder in the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* (DSM-5; American Psychiatric Association; APA, 2013). It consists of two core diagnostic criteria: (a) deficits in social communication and social interaction, and (b) circumscribed, repetitive actions and interests (APA, 2013). According to Baio et al. (2018), ASD is currently estimated to affect 1 in 59 children and shows a higher prevalence in boys than girls (i.e., 4.5:1 ratio). As individual, familial, economic, political, and social costs associated with ASD continue to rise (Lavelle et al., 2014; Leigh & Du, 2015), it is becoming increasingly necessary to develop the most effective and efficient instruments to evaluate and support the best possible outcomes.

One of the current challenges with regard to ASD is finding appropriate measurement tools to assess outcomes in core and associated features of ASD within the intervention context (Lord et al., 2005). Although there are established measures used to diagnose ASD, such as the Autism Diagnostic Interview-Revised (ADI-R; LeCouteur, Lord, & Rutter, 2003) and the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2; Lord, Rutter, DiLavore et al., 2012), there are no comparable measures to assess core and associated features targeted in behavioral ASD interventions (Bolte & Diehl, 2013). This is because of the broad range of symptom manifestation and associated features found in ASD, beyond the more narrow core diagnostic criteria (Brinkley et al., 2007), makes it challenging to effectively measure treatment effects between individuals with such varying symptom presentations. Additionally, ASD diagnostic instruments such as the ADI-R (LeCouteur et al., 2003), and the ADOS-2 (Lord, Rutter, DiLavore et al., 2012) require specific expertise and an extended time frame to administer (Lord, Corsello, & Gradzinski, 2014). They are also expensive, time consuming, and

were not designed to be sensitive enough to measure short-term changes in behavior (Bolte & Diehl, 2013; Brinkley et al., 2007; Lord et al., 2014).

Without established tools to measure treatment effects (i.e., intervention outcomes), researchers often resort to inappropriately using ASD diagnostic instruments and those not specifically designed for the ASD population to measure short-term behavior, symptom, or skills changes (Brinkley et al., 2007; Lord et al., 2014). One particular measure, the Aberrant Behavior Checklist-Community (ABC-C; Aman & Singh, 2017), has emerged as one of the most popular and possibly useful instruments to measure behavior change in children and adults with ASD (Aman & Singh, 2017; Bolte & Diehl, 2013), although it was not initially designed for the ASD population. Intellectual disability (ID) was the population of interest and development for the ABC-C (Aman & Singh, 2017) but it has since been widely adopted for use with individuals with ASD as well.

ASD researchers became intrigued with the ABC-C because its content seemed to reflect a variety of core and associated problematic behaviors found in ASD that are typically the main targets of treatment. However, the ABC-C was put into use by ASD researchers prior to being been factor analyzed for the ASD population. For example, a key psychopharmacological study examining the effects of Risperidone on individuals with ASD (McCracken, 2002) used the ABC-C Irritability subscale as the primary outcome measure. McCracken et al. (2002) was one of the major studies used as justification for the Food and Drug Administration's (FDA) decision to approve Risperidone usage with individuals with ASD in 2006 (Aman & Singh, 2017). Yet, the first factor analytic study of the ABC-C for the ASD population occurred in 2007 (Brinkley et al., 2007).

Prior to the ABC-C, there was an initial version of the scale, The Aberrant Behavior

Checklist (ABC; Aman & Singh, 1986). It was designed to assess the effects of psychoactive drug intervention on unwarranted behaviors in individuals with ID living in residential environments (Aman & Singh, 1986). The authors soon after modified the ABC and developed the Aberrant Behavior Checklist-Community (ABC-C; Aman & Singh, 1994) for use outside of residential institutions in the broader community because institutionalization for individuals with such disabilities became much less frequent over time (Aman & Singh, 1994, 2017). The ABC-C has since been used in both psychopharmacological and behavioral outcome studies (e.g., Hassiotis et al., 2009), many of which involved individuals with ASD.

It is important to highlight that there are key differences that distinguish between individuals with ID and ASD. However, differentiating between the two disorders is often most difficult in individuals who have poorly developed language (APA, 2013). There is also a high comorbidity (about 31%) of individuals with ASD who also have ID (i.e., an IQ of $\leq$ 70; Centers for Disease Control, 2014). Yet, in general, individuals with ASD will often show a very clear discrepancy between their social and communication skills and their cognitive functioning (APA, 2013). Individuals with ASD are also often distinguished from individuals with ID because of their more pronounced adherence to routines, stereotyped and repetitive behaviors, and fixation on parts of objects (Pedersen et al., 2017). Although it can be challenging to differentiate between individuals with ASD and ID, individuals with ASD are best treated and studied as a distinct population.

Thus, given the promise of the ABC-C to help address the need for quality instruments used to measure ASD intervention outcomes (Lord et al., 2005), and its popularity amongst ASD researchers (Bolte & Diehl, 2013), a rigorous investigation of its data structure is warranted. This is necessary in order to clearly determine what constructs the ABC-C is measuring in the

ASD population, in contrast to the ID population for which the ABC-C was initially designed. It is essential to understand how best to organize and score the subtest structures of the instrument so that it can be most effectively implemented with individuals with ASD.

With regard to analyzing a data structure, *factor analysis* has emerged as a primary method for evaluating, summarizing, and understanding the multifaceted patterns and relationships found in psychological measures (Fabrigar & Wegener, 2012; Floyd & Widaman, 1995) like the ABC-C. These factor analytic techniques are used to discern the underlying constructs in instruments in the form of factors (Fabrigar & Wegener, 2012). Exploratory factor analysis (EFA) is regarded as the most useful technique for uncovering these latent constructs in the early stages of instrument development or instrument validation (Osborne & Banjanovic, 2016). Confirmatory factor analysis (CFA) is used to test theorized factor structures that are typically derived from an EFA (Fabrigar & Wegener, 2012). EFA is meant to be exploratory, meaning that it enables one to produce various potential solutions without forcing any strong assumptions about the relationships into the data (Fabrigar & Wegener, 2012). CFA is more limiting and meant to assess the fit of a hypothesized factor structure (Pett, Lackey, & Sullivan, 2003). However, factor analyses in the developmental disability literature have historically had many shortcomings (Norris & Lecavalier, 2010). This is true for the ABC-C as well, as multiple EFAs and CFAs have been performed on the scale yielding varying factor solutions, raising many questions regarding the instrument's most appropriate subscale or score structure.

More specifically, there have only been three EFAs and two CFAs on the ABC-C in samples of those with ASD (i.e., Brinkley et al., 2007; Kaat, Lecavalier, & Aman, 2014; Mirwis, 2011). These three EFAs have resulted in differing factor solutions across the existing studies, with four-, five-, and seven-factor structures. In one of the EFAs, a study by Brinkley et al.

(2007), only four-and five-factor structures were considered as possible solutions, limiting exploration of other interpretable solutions that could have emerged from the data. In Kaat et al., (2014) it appears that a questionable factor solution selection rationale resulted in retention of a five-factor solution consistent with expectations of the ABC-C authors. Further, only one study, Mirwis (2011), used agency/special educational staff to rate participants, as the other two factor analytic studies used parents/caregivers as raters. This is potentially important as the rater brings her own unique perspectives to ratings and can influence outcomes (Hoyt, 2000). Raters from a special education environment might interpret questions differently than parents or caregivers who know their children in a separate context. Additionally, as research has shown, context can influence rater behavior as well (Tziner, Murphy, & Cleveland, 2005).

With regard to the two CFAs on samples of those with ASD (Brinkley et al., 2007; Kaat et al., 2014), only Kaat et al. (2014) examined multiple factor solutions (four-, five-, and six-factor solutions). Neither Kaat et al. (2014) nor Brinkley et al. (2007) found a strong model fit with the solutions they examined. Additionally, the seven-factor solution found in Mirwis (2011) was not included in the analysis by Kaat et al. (2014). Thus, performing a rigorous EFA analysis and generating a robust model first, followed by performing a CFA on this new model and examining all previous theorized models—including the solution generated by Mirwis (2011)—will enable the best factor structure, in terms of absolute and relative fit, to emerge for the ABC-C for individuals with ASD.

Overall, the purpose of this study is to examine the factor structure of the ABC-C using an ASD sample rated by special education staff members to address the following four gaps in the literature: a lack of sufficient research performed on the factor structure of the ABC-C with ASD samples; a failure in the current literature to explore alternative factor structures in the

EFAs of the ABC-C and in turn to examine more of these models in a CFA; only one study (Mirwis, 2011) has used special education staff members as raters with an ASD sample resulting in a unique seven-factor structure, raising the question about whether raters in this environment can influence a different factor structure; and no study has performed a CFA on the ABC-C directly comparing all the models generated with ASD samples (i.e., Brinkley et al., 2007 Kaat et al., 2014; Mirwis, 2011).

The exploratory portion of the study will investigate a range of possible factor structures—giving a better sense of what degree the five-subscale interpretative structure proposed by the ABC-C authors is suitably generalizable to individuals with ASD or if an alternative structure would better capture variation in item ratings among those with ASD. The confirmatory part of the study will test the fit of the factor model generated in the EFA against the existing proposed factor models for individuals with ASD. Performing both an EFA and CFA, this study will address existing methodological shortcomings in the ABC-C psychometric literature and contribute another exploratory and confirmatory analysis to the currently limited number of rigorous factor analytic studies of the ABC-C for individuals with ASD. The study is particularly important for individuals within the ASD population who require the most intensive levels of support (i.e., individuals with impaired verbal and nonverbal communication with little to no intelligible speech and severe restricted, repetitive behaviors) who would most benefit from a measure that is able to assess changes in their behavior over time. Thus, given the role the ABC-C has played as a key outcome measure in various behavioral and psychopharmacological studies for individuals with ASD and its popularity amongst ASD researchers (Bolte & Diehl, 2013), it is critical to illuminate the most suitable factor structure for the ASD population. This will help to address the concern that the default scoring structure of the ABC-C may not be

appropriate for, or fully represent the range of constructs assessed by the ABC-C in those with ASD.

CHAPTER 2: LITERATURE REVIEW

Introduction

Autism Spectrum Disorder (ASD) is estimated to affect 1 in 59 children, with rates higher in boys than girls (4.5:1; Baio et al., 2018). Leigh and Du (2015) estimated that societal costs for ASD (i.e., medical and non-medical interventions and productivity loss for caregivers and individuals with ASD) were approximately $268.3 billion in 2015 or 1.5% of United States gross domestic product (GDP). The authors projected that the societal cost for ASD will rise to $460.8 billion, or 1.6% of GDP, by 2025, becoming a greater economic expenditure than Attention-deficit/hyperactivity disorder (ADHD) and diabetes (Leigh & Du, 2015). Further, Lavelle et al. (2014) found that taking care of a child with ASD, factoring in a variety of associated care expenses, resulted in an estimated extra $17,081 per year. In addition, political and social complexities associated with individuals with ASD have arisen as well, such as disability rights issues and inclusionary challenges (Ripamonti, 2016). Put simply, individuals with ASD have had a tangible impact on the economic, political, and social elements of US society.

ASD is classified as a neurodevelopmental disorder, with symptoms typically apparent early in development (APA, 2013). Core characteristics of ASD involve deficits with regard to social communication and interaction as well as the presence of "restricted, repetitive patterns of behavior, interests, or activities" (APA, 2013, p. 31). ASD is conceptualized as a spectrum of behaviors that can manifest in various ways depending upon the severity of an individual's particular deficits, stage of development, and the presence of certain associated features. Conceptualization of ASD has evolved since the original description by Kanner (1943), as experts have attempted to grasp the heterogeneity of symptomology (Volkmar, Reichow,

Westphal, & Mandell, 2014). Despite the myriad forms that ASD takes, individuals are now categorized based on the severity level of functional support needs with regard to social communication, and restricted, repetitive behaviors (APA, 2013).

Individuals with ASD who require the lowest levels of support refers to individuals who have clear impairments in social communication (e.g., problems with initiating conversation, engaging in social reciprocity, and making friends), and challenges with regard to restricted, repetitive behaviors (e.g., inflexibility in particular contexts, and difficulty with transitions; APA, 2013). Prior to the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* (DSM-5; American Psychiatric Association; APA, 2013), individuals with symptoms of autism who required less intensive supports were often diagnosed with Asperger's disorder, high-functioning *autistic disorder*, or high-functioning *pervasive developmental disorder-not otherwise specified* (PDD-NOS; Volker, Thommer, & Lopata, 2010). Once IQ and developmental language levels were accounted for, other qualitative differences between autistic disorder, Asperger's disorder, and PDD-NOS—all no longer found in the DSM-5 (APA, 2013)—were not substantive (Witwer & Lecavalier, 2008). The differences between the disorders were found to be ambiguous and based more on symptom severity rather than dissimilarities among core symptoms. As a result, clinicians were not making reliable diagnostic distinctions between disorders (Lord, Petkova, Hus et al., 2012), ultimately leading to the singular spectrum category, ASD, now found in the DSM-5 (APA, 2013). Of note, for this study, the focus will primarily be on individuals who require more substantial supports as a result of more severe deficits in social communication and restricted, repetitive behaviors; however, all individuals included required supports resulting from deficits in functional impairments severe enough to necessitate their inclusion in special education classrooms.

Diagnosis of individuals with ASD requiring more intensive supports. Although diagnosis of ASD is challenging across the spectrum, given the wide range of core and comorbid symptom presentation and intensity (Huerta & Lord, 2012), individuals who require more significant supports are more likely to be identified according to the DSM-5 (APA, 2013) ASD criteria than individuals who require less significant supports (McPartland, Reichow, Volkmar, 2012). Early signs of individuals with more severe symptomology with ASD can often be seen in the first or second year of life through developmental delays in language, and social interaction (APA, 2013). These symptoms, though typically screened for in pediatric checkup visits (and then further assessed more intensively if necessary), are still often under-identified given the wide range of individual presentation and intensity (Huerta & Lord, 2012).

Diagnosis of ASD

Core diagnostic criteria and associated features of ASD. Assessing ASD is complicated (Huerta & Lord, 2012). Different types of instruments have been developed specifically for that undertaking, including observational systems, behavior rating scales, retrospective rating scales, and structured interviews for current and past functioning. All of these instruments are ultimately tied to the DSM-5 (APA, 2013), considered the central diagnostic resource used by clinicians and researchers. Because the scope of this study encompasses a change from an earlier version of the *Diagnostic and Statistical Manual of Mental Disorders, fourth edition, text revision* (DSM-IV-TR; APA, 2000) to the current version (DSM-5; APA, 2013), criteria for diagnosing ASD for both versions are presented here.

DSM-IV-TR diagnostic criteria. The DSM-IV-TR (APA, 2000) lists five disorders with symptoms of autism under the Pervasive Developmental Disorders (PDDs) category: Rett's disorder, childhood disintegrative disorder (CDD), Asperger's disorder, PDD-NOS, and autistic

disorder (APA, 2000). Rett's disorder, which involves a number of distinctive features, was found to have a genetic basis (Amir et al., 1999) setting it apart from the autism spectrum and is now considered a distinct progressive neurological disorder (Volkmar, et al., 2014). CDD, included in the DSM-IV-TR (APA, 2000) essentially for research purposes (Volkmar et al., 2014), has also been removed from the DSM-5 (APA, 2013) given disputes about its validity as a disorder that is different from ASD (Volker et al., 2010). Asperger's disorder was the diagnostic classification typically applied to individuals with symptoms of autism (i.e., challenges with social interactions) but intact cognitive, linguistic, and adaptive skills (Volker et al., 2010). PDD-NOS was the diagnosis applied to individuals who did not meet full criteria for any of the other PDDs but still exhibited significant symptoms of autism (Volker et al., 2010). Individuals diagnosed with autistic disorder, Asperger's disorder, or PDD-NOS under the *Diagnostic and Statistical Manual of Mental Disorders, fourth edition* (DSM-IV APA, 1994) and the DSM-IV-TR (APA, 2000) were subsequently subsumed under the criteria for ASD in the DSM-5 (APA, 2013). As such, only the core diagnostic features of autistic disorder will be highlighted in this section, as research has shown (e.g., Witwer & Lecavalier, 2008) Asperger's disorder and PDD-NOS to be essentially indistinguishable.

In order to have obtained a diagnosis of autistic disorder in the DSM-IV-TR (APA, 2000), three core features must have been met: "qualitative impairment in social interaction" and "communication", as well as evidence of "restricted repetitive and stereotyped patterns of behavior, interests, and activities" (APA, 2000, p. 75). A diagnosis must also have included developmental delays or atypical behavior prior to age three with regard to "social interaction," or "language as used in social communication," or "symbolic or imaginative play" (APA, 2000, p. 75)

To have met diagnostic criteria for “impairment in social interaction” in the DSM-IV-TR (APA, 2000), individuals must have demonstrated at least two of the following symptoms: noticeable challenges with various nonverbal behaviors (e.g., eye gaze, physical posture); lack of success in creating age-appropriate, peer relationships; absence of “spontaneous seeking to share enjoyment, interests, or achievements” with others, and a lack of “social or emotional reciprocity” (APA, 2000, p. 75). To have met diagnostic criteria for “qualitative impairments in communication,” individuals must have shown only one of the following symptoms: “delay in, or total lack of, the development of spoken language,” without attempting to communicate via other non-verbal behaviors; challenges for individuals with “adequate speech” with regard to their skills in initiating or maintaining dialogue; “stereotyped and repetitive use of language or idiosyncratic language”; and lack of or limited “spontaneous make-believe play or social imitative play” suitable for the individual’s “developmental level” (APA, 2000, p. 75). To have met diagnostic criteria for “restricted repetitive and stereotyped patterns of behavior, interests, and activities,” individuals must have displayed at least one of the following symptoms: fixation “with one or more stereotyped and restricted patterns of interest” considered to be atypical “either in intensity or focus”; seemingly rigid observance to particular, “nonfunctional routines or rituals”; “stereotyped and repetitive motor mannerisms”; and “persistent” fixation with “parts of objects” (APA, 2000, p. 75).

Thus, the DSM-IV-TR (APA, 2000) established that difficulties with social interaction, communication, and restricted, repetitive and stereotyped patterns of behavior were essential to the autistic disorder diagnosis—which was viewed as the full manifestation of a syndrome, or extreme end of a spectrum, which the other ASDs among the PDDs appeared to only partially manifest. However, as subsequent research on the autism spectrum population progressed, it

became apparent that diagnostic parameters needed to be modified and broadened to allow the other ASD-related diagnoses (i.e., Asperger's Disorder, and PDD-NOS) to be included with autistic disorder under a larger diagnostic umbrella.

DSM-5 diagnostic criteria. The DSM-5 (APA, 2013), released in 2013, changed the emphasis of core features for the diagnoses of ASD. In order to obtain a diagnosis of ASD in the DSM-5 (APA, 2013), two core features must be met: "persistent deficits in social communication and social interaction across multiple contexts" and "restricted, repetitive patterns of behavior, interests, or activities" (APA, 2013, p. 50). Each of these core criteria is also to be assigned one of three increasingly intensive levels of current severity. Level one signifies "requiring support," level two signifies "requiring substantial support," and level three signifies "requiring very substantial support" (APA, 2013, p. 52). Individuals require supports to be in place to accommodate for impairments if they have a level one severity in social communication (e.g., initiating social interactions, making friends, and challenges with social reciprocity), and with restricted, repetitive behaviors (e.g., inflexibility in particular contexts, difficulties with organization and planning; APA, 2013). Individuals require more significant supports to be in place to accommodate for impairments if they have a level two severity in social communication (e.g., noticeable deficits in verbal and nonverbal social communication even with supports, atypical nonverbal communication and lack of social initiation) and with restricted, repetitive behaviors (e.g., challenges dealing with change, restricted or stereotypic behaviors that are readily apparent and hinder functioning in multiple environments; APA, 2013). Individuals require the most intensive level of support in place to accommodate for impairments if they have a level three severity in social communication (e.g., intensive deficits in verbal and nonverbal communication that result in major impairments in functioning such as an

individual with little to no intelligible speech) and with restricted, repetitive behaviors (e.g., major challenges coping with change and restricted or stereotypic behavior that negatively affects functioning in all contexts; APA, 2013). Diagnosis must also include the fact that symptomology had to exist during the "early developmental period" even if it may not be greatly pronounced "until social demands exceed limited capacities, or may be masked by learned strategies later in life," and the fact that symptomology has to result in "clinically significant impairment in social, occupational, or other important areas of current functioning" (APA, 2013, p. 50). The DSM-5 (APA, 2013) also specifies that individuals who received diagnoses under the DSM-IV-TR (APA, 2000) of autistic disorder, Asperger's disorder, or PDD-NOS would now assume an ASD diagnosis (APA, 2013, p. 51).

To meet diagnostic criteria for "persistent deficits in social communication and social interaction across multiple contexts" individuals must demonstrate all three of the following behaviors either presently or historically. First individuals must have "deficits in social-emotional reciprocity" that can span from exhibiting atypical social interaction and lack of typical conversational exchange to portraying limited "sharing of interests, emotions, or affect," and even displaying a failure to originate or respond to social exchanges (APA, 2013, p. 50). Second, individuals must have "deficits in nonverbal communicative behaviors used for social interaction" that can span from having inadequate verbal and nonverbal communication skills to irregularities with regard to "eye contact and body language" and challenges in comprehending and utilizing gestures, and a complete absence of "facial expression and nonverbal communication" (APA, 2013, p. 50). Third, individuals must have "deficits in developing, maintaining, and understanding relationships" spanning from challenges adapting behavior to be

appropriate in different social environments to "difficulties in sharing imaginative play or in making friends" to a lack of curiosity in peers (APA, 2013, p. 50).

To meet diagnostic criteria for "restricted, repetitive patterns of behavior, interests, or activities" individuals must demonstrate at least two of four specific behaviors—either presently or historically. First, demonstrating "stereotyped or repetitive motor movements, use of objects, or speech" (APA, 2013, p. 50). Second, portraying an "insistence on sameness, inflexible adherence to routines, or ritualized patterns of verbal or nonverbal behavior" (APA, 2013, p. 50). Third, displaying extremely limited and "fixated interests" that are atypical in "intensity or focus" (APA, 2013, p. 50). Fourth, exhibiting "hyper-or hyporeactivity to sensory input or unusual interest in sensory aspects of the environment" (APA, 2013, p. 50).

In addition to core features, discussed above, the DSM-5 (APA, 2013) highlights various associated or comorbid features that are often present in individuals with ASD. These include, cognitive and linguistic deficits, motor impairments, anxiety, depression, and catatonic motor behavioral occurrences (e.g., "mutism, posturing, grimacing, and waxy flexibility"; APA, 2013, p. 55). The DSM-5 (APA, 2013) also indicates that self-injury ("e.g., head banging, biting the wrist") is found in some individuals with ASD, with "disruptive/challenging behaviors more common in children and adolescents with ASD than other disorders, including intellectual disability" (APA, 2013, p. 55).

Differentiating ASD and intellectual disability. The DSM-5 (APA, 2013) highlights a differential diagnosis between intellectual disability (ID) and ASD by noting that ASD is the more suitable diagnosis when there is a clear incongruity "between the level of social-communicative skills and other intellectual skills" (p. 58). However, as pointed out in the DSM-5 (APA, 2013), differentiating between ASD and ID can be especially difficult in individuals

who have poorly developed language and "symbolic skills" because stereotypic behavior is often common with individuals with both disorders (p. 58). According to the Centers for Disease Control (CDC; 2014), 31% of individuals with ASD had IQ scores $\leq$ 70 (in the ID range) and 23% had IQ scores between 71-85 (in the borderline range). Thus, there is a common comorbidity between ASD and ID; yet, despite these high rates, researchers have found distinct differences between individuals with ASD and ID.

Pedersen et al. (2017) performed and area under the curve analysis to determine which specific diagnostic differences could be distinguished between individuals with ASD and ID. The authors found that adherence to routines, stereotyped and repetitive behaviors, and fixation on parts of objects were most discriminatory between the two groups. Spoken language and conversation difficulties were less distinctive between the diagnoses (Pedersen et al., 2017). Kraper, Kenworthy, Popal, Martin, & Wallace (2017) found adaptive behavior skills in individuals with ASD with IQ's $\geq$ 70 to be significantly lower than normative peers. Further, the authors found an inverse relationship between IQ and adaptive behavior in individuals with ASD in that the greater the differences between IQ and adaptive functioning (e.g., higher IQ, lower adaptive functioning), the higher the levels of depression, anxiety, and social challenges. Kurzius-Spencer et al. (2018) looked at behavior issues in children with ASD with and without a comorbid ID. They found that children with comorbid ASD and ID were at a higher risk of self-injurious behavior, atypical fear reactions, and eating issues, but also found decreases in issues with mood in individuals with lower IQ. Further, Kurzius-Spencer et al. (2018) found that in children with ASD, the level of cognitive impairment was not related to the chance of "inattention/hyperactivity, aggression, argumentative/oppositional behavior, temper tantrums, or unusual sensory responses" (p. 67). Of note, research is mixed with regard to the effects of

comorbid ID and ASD with some recent studies (e.g., Goldin, Matson, & Cervantes, 2014) also showing no significant effects on various behaviors (e.g., tantrums, stereotypic behavior, depression/anxiety, conduct issues) compared to individuals with ASD only.

Overall, despite certain overlapping similarities between the disorders, research has shown that there are distinct differences between individuals with ASD and ID. Nevertheless, it remains challenging to distinguish between persons with ASD and ID, particularly from a measurement perspective amongst individuals requiring the most extensive supports. As such, the disorders themselves warrant further studying both separately and when they occur in a comorbid fashion.

DSM-IV-TR to DSM-5 changes for ASD. Changes from the DSM-IV-TR (APA, 2000) to DSM-5 (APA, 2013) have engendered a variety of research and clinical implications due to differences in emphasis of core features and the broadening to a *spectrum* nosology that now captures several other diagnostic categories present in the DSM-IV-TR (APA, 2000; Lecavalier, 2013; Volkmar et al., 2014). The major modifications included reducing the core symptom domains from social, communication, and restricted, repetitive behavior to social-communication (without requiring language delay) and restricted, repetitive behavior; expanding the diagnostic options with greater developmental sensitivity such that diagnostic symptomology could be met historically and did not need to be currently present; using specifiers (e.g., symptom severity, intellectual impairment) instead of the previous DSM-IV-TR (APA, 2000) axial system; and, perhaps the most fundamental of all the changes, removing the PDD category completely in favor of an overarching category of *Autism Spectrum Disorder* (ASD). In essence, three of the five PDD subcategories (Asperger's disorder, autistic disorder, PDD-NOS) were subsumed under the ASD classification in DSM-5 (APA, 2013). Rett's disorder was subsequently removed

from the DSM-5 and childhood disintegrative disorder (CDD) was conceptualized as a later-onset ASD (Lord & Jones, 2012; Volker, 2012).

According to Volkmar et al. (2014), justification for condensing the three core symptom domains to two included factor analyses (e.g., Norris, Lecavalier, & Edwards, 2012) showing the DSM-5 (APA, 2013) two-symptom model performing as well as the DSM-IV (APA, 1994) three-symptom model. According to Lai, Lombardo, Chakrabarti, and Baron-Cohen (2013) the expansion of ASD symptom criteria in DSM-5 (APA, 2013) to meet a historical standard rather than be currently present resulted from a desire to improve diagnostic reliability (e.g., Lord & Jones, 2012). Clinicians and researchers determined that while ASD is understood as a lifelong disorder, symptomology may not be recognized for all individuals until environmental demands exceed individual skill level. The move in DSM-5 (APA, 2013) to include specifiers (e.g., language impairment and symptom severity) for the ASD diagnosis added pertinent clinical information to the diagnostic category to inform both research and practice (Happé, 2011; Lai et al., 2013). Thus, as Happé (2011) explained, the large symptom variability exhibited by individuals now falling within the new, broad, spectrum diagnostic category in the DSM-5 would be accounted for alongside the "essential shared features of the autism spectrum" diagnosis as well (p. 541). Overall, research support for the changes from DSM-IV-TR (APA, 2000) to DSM-5 (APA, 2013) included evidence of increased sensitivity and a slight decrease in specificity for an ASD diagnosis (e.g., Frazier et al., 2012; Huerta, Bishop, Duncan, Hus, & Lord, 2012; Mazefsky, McPartland, Gastgeb, & Minshew, 2013; Volkmar et al., 2014).

The conceptual changes that occurred in the APA's official diagnosis of ASD from DSM-IV-TR (APA, 2000) to DSM-5 (APA 2013) meant that clinicians and researchers had to adapt their understanding and practices to accommodate for the new disorder. Part of this change involved

assessing whether the associated instruments that they used with regard to ASD would still be appropriate and effective. Although no instrument is ever perfectly constructed, standards and guidelines have been established to assist developers in making the highest possible quality measures. These standards are also helpful in assessing whether developers of existing instruments have taken the necessary steps to produce measures that are effective for the way that they are currently used.

Standards for Validity, Fairness, Test Design and Development

The *Standards for Educational and Psychological Testing (SEPT; 2014)* offers guidelines for test development and usage. Authored by the American Educational Research Association, the APA, and the National Council on Measurement in Education, the SEPT was developed in order to establish a solid foundation by which to examine the validity of test outcomes. It is intended for both test developers and users as well as for researchers who examine test properties. Although these standards are most appropriately applied to standardized measures (e.g., cognitive or achievement tests), the authors highlight that they can still be helpful with regard to a wide range of instruments (SEPT, 2014).

The SEPT addresses key testing topics including validity, reliability, fairness, design and development, scores and norms, administration, and rights and responsibilities of test takers and users (SEPT, 2014). As the authors point out, the SEPT is not meant to be a checklist nor is it expected for every test to satisfy every standard in the SEPT, but rather that the spirit of the standards be maintained. The authors highlight the fact that the field of testing is constantly developing and that the SEPT requires periodic revision (SEPT, 2014). Examples of SEPT standards most relevant to this study for validity, fairness, and test design and development are provided in Table 1, Table 2 and Table 3.

Table 1. *Examples of Standards For Validity*

Cluster	Standard Number	Standard
Establishing Intended Uses and Interpretations	1.1	The test developer should set forth clearly how test scores are intended to be interpreted and consequently used. The population(s) for which a test is intended should be delimited clearly and the construct or constructs that the test is intended to assess should be described clearly.
Establishing Intended Uses and Interpretations	1.3	If validity for some common or likely interpretation for a given use has not been evaluated, or if such an interpretation is inconsistent with available evidence, that fact should be made clear and potential users should be strongly cautioned about making unsupported interpretations.
Establishing Intended Uses and Interpretations	1.4	If a test score is interpreted for a given use in a way that has not been validated, it is incumbent on the user to justify the new interpretation for that use, providing a rationale and collecting new evidence if necessary.

Examples of the SEPT with regard to *Validity* in Table 1 highlight the importance of tests to make clear the populations with which they are intended to be used. These selected standards with regard to *Establishing Intended Uses and Interpretations* seem to emphasize the fact that tests are developed with particular populations in mind. Thus, if users implement a test with a different population, the validity of the test outcome is called into question. This is not to say that a test can never be given or even valid with a different population than it was originally intended, but rather, that interpretations of testing outcomes are potentially different for different populations. Assuming or generalizing outcome interpretability across populations without appropriate evidence is unfounded. Moreover, as is suggested in standard 1.4, if a test is used in a different way or used in a different situation, then expert judgment is necessary to determine whether the existing validity information can be appropriately used in the new situation. That new situation could certainly affect the validity of the instrument and thus, as the standard shows, new evidence may be necessary to collect.

Table 2. *Examples of Standards For Fairness*

Cluster	Standard Number	Standard
Test Design, Development, Administration, and Scoring Procedures That Minimize Barriers to Valid Score Interpretations for the Widest Possible Range of Individuals and Relevant Subgroups	3.3	Those responsible for test development should include relevant subgroups in validity, reliability/precision, and other preliminary studies used when constructing the test.

An example of the SEPT with regard to *Fairness* in Table 2 highlights the need for test developers to include pertinent subgroups when developing tests (SEPT, 2014). This should be done in order to best capture those subjects who might significantly alter testing interpretations (and outcomes) due to their potentially unique responses to different aspects of a test (e.g., content, test design, and format). By implication, without doing this work, developers leave themselves vulnerable to creating tests that lack adequate validity or reliability for their intended populations.

Table 3. *Examples of Standards For Test Design and Development*

Cluster	Standard Number	Standard
n/a	4.0	Tests and testing programs should be designed and developed in a way that supports the validity of interpretations of the test scores for their intended uses. Test developers and publishers should document steps taken during the design and development process to provide evidence of fairness, reliability, and validity for intended uses for individuals in the intended examinee population.
Standards for Test Specifications	4.1	Test specifications should describe the purpose(s) of the test, the definition of the construct or domain measured, the intended examinee population, and interpretations for intended uses. The specifications should include a rationale supporting the interpretations and uses of test results for the intended purpose(s).

Table 3 (cont'd)

Standards for Test Specifications	4.6	When appropriate to documenting the validity of test score interpretations for intended uses, relevant experts external to the testing program should review the test specifications to evaluate their appropriateness for intended uses of the test scores and fairness for intended test takers. The purpose of the review, the process by which the review is conducted, and the results of the review should be documented. The qualifications, relevant experiences, and demographic characteristics of expert judges should also be documented.
Standards for Test Revision	4.24	Test specifications should be amended or revised when new research data, significant changes in the domain represented, or newly recommended conditions of test use may reduce the validity of test score interpretations. Although a test that remains useful need not be withdrawn or revised simply because of the passage of time, test developers and test publishers are responsible for monitoring changing conditions and for amending, revising, or withdrawing the test as indicated.

Examples of the SEPT with regard to *Test Design and Development* in Table 3 highlight some similar ideas as found in the SEPT with regard to *Validity*, though they focus more specifically on test development (SEPT, 2014). For instance standard 4.24 highlights the importance of re-examining and potentially revising a test as the need arises, particularly if new data becomes available that potentially calls into question a test's existing interpretations. The authors point out that this is not to say that an older version of a test is always invalid, rather, that it is incumbent upon the user to justify the use of an older version of a test in spite of the existence of a newer version (SEPT, 2014). The authors also seem to imply with this standard the need for test developers and users to embrace one of the core ideals of the SEPT that tests must evolve as populations and conditions change over time in order to maintain their level of rigor.

Overall, the SEPT (2014) is a valuable tool to help developers and users achieve high standards with regard to test development and usage. Following the SEPT (2014) however does not ensure that a test will always be of the best possible quality. Multiple factors can complicate this process. This is particularly true with regard to ASD and the difficulties that developers,

researchers, and users encounter given the wide-range of symptoms and varying presentations associated with the disorder.

Assessment: Diagnosis and Monitoring

Given the broad range of possible behaviors associated with ASD, differential diagnosis can be complicated (Trammell, Wilczynski, Dale, & McIntosh, 2013). Clinicians often struggle to determine whether particular symptom presentations result from core social-communication deficits and repetitive behaviors, or whether behaviors are better explained by other disorders, or if the behavior presentation reflects a combination of ASD and one or more comorbid disorders. The DSM-5 (APA, 2013) lists various differential diagnoses for ASD: Rett syndrome, selective mutism, language disorders and social communication disorder, intellectual disability, stereotypic movement disorder, ADHD, and schizophrenia (APA, 2013). Yet, there are no objective measures specifically designed to address comorbidity for individuals with ASD (Trammell et al., 2013). The key factors that complicate an ASD diagnosis include different symptom presentations at various ages and developmental levels (Huerta & Lord, 2012; Matson, Beighley, & Turygin, 2012), a wide range of cognitive levels (Huerta & Lord, 2012), the challenge of assessing the impact of language delays (Lord et al., 2014), a lack of diagnostic measures available specifically designed for adolescents and adults (Trammell et al., 2013), and difficulties with deriving appropriate normative groups (e.g., chronological age is an insufficient comparison variable given the range of cognitive differences in ASD; Lord et al., 2014). As Lord et al. (2014) stated, overall, assessment tools for ASD have been relatively accurate for identifying ASD in "somewhat verbal, mildly to moderately intellectually disabled, school age children" (p. 612). The authors argued that assessing individuals outside of the "4 to 12 year-old" age group "with some but not fluent speech" is still challenging (Lord et al., 2014, p. 612).

According to the DSM-5 (APA, 2013) using input from a variety of data sources is the most valid and defensible way to assess for ASD. Such data can include information obtained through clinical observations, caretaker perspectives, and even from individual self-report. As Huerta and Lord (2012) explained, caretaker perspectives enable a clinician to understand an individual's functioning both historically and in multiple environments, while observation allows a clinician to directly assess the presence of specific skills and deficits. Yet, as Falkmer, Anderson, Falkmer, and Horlin (2013) stated, because an ASD diagnosis can only be determined through assessment of behavior symptoms, there will inevitably be weaknesses and biases with regard to individual source interpretations (Falkmer et al., 2013). Key to the methods and instruments that are ultimately chosen are the goals of assessment, such as for general information, screening, diagnostic input, or to determine the intensity of intervention needs (Lord et al., 2014). An ASD diagnosis typically involves an initial screening, using less time-consuming and more cost-effective methods (e.g., a brief parent rating scale), followed by a more extensive diagnostic confirmation process involving multiple assessment methods (Hampton & Strand, 2015). Common assessment methods include interviews, observations, and rating scales (Lord et al., 2014).

Interviewing and observational instruments. Interviewing, both formally and informally, enables a clinician to obtain both contextual and historical information concerning an individual's behavior and development (Huerta & Lord, 2012). Additionally, interviewing offers a clinician the opportunity to be flexible and spontaneous, or maintain a structured or semi-structured format (Merrell, 2001). The most often currently used diagnostic interview instrument for ASD is the Autism Diagnostic Interview-Revised (ADI-R; LeCouteur, Lord, & Rutter, 2003). It is a semi-structured interview for caregivers, capturing behaviors currently and at the time

most likely to have displayed ASD-like symptoms, around age four to five years. The instrument is found to have good psychometric properties, but limited sensitivity with individuals with very low IQ and mental age (Lord et al., 2014; Ozonoff, Goodlin-Jones, Solomon, 2005). In addition, the administration time can be too time consuming for many clinicians (Ozonoff et al., 2005).

The ADI-R (LeCouteur et al., 2003) is often used in conjunction with an observational system, the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2; Lord, Rutter, DiLavore et al., 2012). Clinicians use a protocol of structured or semi-structured interaction involving "social interaction, communication, and play," which takes around 30-45 minutes. The protocol is then scored according to diagnostic algorithms (Lord et al., 2014, p. 644). Considerable experience with and knowledge about individuals with ASD are necessary in order to effectively administer and score the assessment (Lord et al., 2014). When used in combination, both the ADOS-2 (Lord, Rutter, DiLavore et al., 2012) and the ADI-R (LeCouteur et al., 2003) are considered the most sensitive and specific diagnostic instruments for ASD (Falkmer et al., 2013), but drawbacks include difficulty in differential diagnosis of ASD and ID for children with limited verbalizations.

Although interview and observational instruments are more comprehensive, there is also a place for rating scales, which unlike interviews and observations, are quick and do not require extensive training. Most often, rating scales are used as screeners in advance of a more comprehensive assessment (Norris & Lecavalier, 2010a). Yet, rating scales have an additional utility in that they can be used to track behavior changes over time.

Rating scales in ASD. Rating scales are used for various purposes. For instance, they can be used for diagnostic reasons and screen for atypical development using a broad-based

approach (e.g., the 'atypicality' scale on the Behavior Assessment Rating Scale for Children, Third Edition [BASC-3; Reynolds & Kamphaus, 2015]), or they can be used to identify symptoms of a particular disorder like ASD, such as with the Gilliam Autism Rating Scale, Second Edition (GARS-2; Gilliam, 2006). Rating scales are efficient with regard to administration time and training, and give voice to multiple stakeholders (Merrill, 2001). However, they do have some disadvantages as well, as ratings are ultimately more subjective appraisals and limited in terms of their validity with various populations, including individuals of different ages and levels of functioning (Lord et al., 2014; Norris & Lecavalier, 2010a).

A key aspect of any rating scale involves the performance of the rater herself (Portney & Watkins, 2000). The rater is responsible for making a subjective assessment based upon some standardized parameters (e.g., a particular scoring scale). Portney and Watkins (2000) highlight the fact that raters must be consistent in the way that they make their judgments otherwise they can negatively affect a scale's validity. That said, as Hoyt (2000) explains, rater bias, or incongruities between raters, is a common problem as raters often bring their own unique perspectives to ratings and can understand questions differently or have distinctive individualized responses to particular stimuli. Depending upon the rated constructs, the raters' training, and the extent of the possibilities of interpretation can result in a range of conceivable impacts on rated outcomes (Hoyt, 2000). Further, research has also shown that context can influence rater behavior (Tziner, Murphy, & Cleveland, 2005) and that various other facets must be examined, such as the environment in which ratings take place, before reliability of a rating scale can be generalized (Portney & Watkins, 2000).

Hoyt (2000) states that ratings performed by multiple raters on the same subject can result in different outcomes for various reasons. This could include discrepancies in the focus

different raters have on particular aspects of a subject, or distinctive occasions under which their ratings occurred (Hoyt, 2000). For instance parents who rate a child's behavior at home might result in a very different rating than if the same child was rated at school by his teacher. A child's behavior could be vastly different in these separate contexts, especially on different days. Parents and teachers might also appraise similar behaviors in dissimilar ways as each rater might be attuned to distinct aspects of the child's behavior in their respective environments.

An example of a commonly used broad-based rating scale that is useful for initially screening individuals at risk for ASD is the Social Responsiveness Scale, Second Edition (SRS-2; Constantino & Gruber, 2012). It is filled out by a caretaker or teacher and is designed to assess social as well as more general behavioral impairments, many of which are associated with core features of ASD. It has strong psychometric properties and is quickly implemented, though it has been found that behavior problems in both individuals with and without ASD result in more of the variance in scores than core symptoms of autism or even social deficits (Lord et al., 2014). In contrast, the Childhood Autism Rating Scale (CARS; Schopler, Reichler, & Renner, 1986) is an example of a commonly used rating scale that was developed to assess for behaviors specifically associated with ASD (Lord et al., 2014). It was designed to be completed by clinicians after observing an individual suspected of ASD. The CARS (Schopler et al., 1986) is particularly good with differentiating between individuals with and without ASD, though it has been found to have difficulties in identifying individuals requiring fewer supports with ASD (Lord et al., 2014).

Rating scales are also relied upon to measure changes in behavior—to track symptoms in response to developmental or intervention-driven change (Bolte & Diehl, 2013). These scales are used to help to determine whether interventions have directly or indirectly had successful

effects on particular skills (Lord et al., 2005). However, despite the large number of instruments used to measure ASD symptomology, there is still a great challenge in effectively assessing treatment affects (Bolt & Diehl, 2013).

Monitoring behavior change. Researchers have used a number of different instruments in attempting to measure core and associated behaviors related to ASD (McConachie et al., 2015). For instance, McConachie et al. (2015) performed a systematic review of assessment tools for young children with ASD and classified 41 instruments in multiple conceptual domains including "autism symptom severity," "global measure of outcome," "social awareness," "restricted and repetitive behaviour and interests," "sensory processing," "language," "cognitive ability," "emotional regulation," "play," "behaviour problems," "global measure of functioning," and "parent stress" (p. xxvi-xxvii). Further, Bolte and Diehl (2013) found 289 "unique measurement tools" and developed 14 conceptual categories, in an approach similar to McConachie et al. (2015). Thus, the large number of instruments used to assess ASD symptomology reflects one of the major challenges associated with the disorder, meaning that the wide range of symptoms and their varying intensities (consisting of both core and associated features) found underneath an umbrella-like classification such as ASD, makes it difficult to effectively measure treatment effects (Bolte & Diehl, 2013). This has lead researchers to try multiple unique ways to address this challenge (Bolte & Diehl, 2013).

As Bolte and Diehl (2013) illustrated, one of the core ASD symptoms, "restricted, repetitive patterns of behavior, interests, or activities," can present in vastly different ways across individuals (APA, 2013, p. 51). This can be exhibited in the form of rigid routines and schedules, speech repetition, repetitive physical movement, or even a circumscribed interest in a certain subject (Bolte & Diehl, 2013). Thus, researchers have had to develop and employ

multiple instruments in order to try and address their specific intervention outcome measurement needs. In fact, Bolte and Diehl (2013) found that from 2001 to 2010, 61.6% of the instruments used to measure outcomes were used in only one study. This makes comparing results across studies more difficult, with so many different measures being employed (Bolte & Diehl, 2013).

Unlike the two most acclaimed instruments used to diagnose ASD, the ADOS-2 (Lord, Rutter, DiLavore et al., 2012) and the ADI-R (LeCouteur et al., 2003), there are no equivalent, established measures to assess behavioral outcomes for ASD interventions (Bolte & Diehl, 2013). As Lord et al. (2014) elucidated, the ASD diagnostic instruments were not developed to be sensitive to short-term behavior changes and were not designed to measure changes in behavior particularly as individuals get older and their environments and behavioral expectations change. Brinkley et al. (2007) pointed out that using ASD diagnostic measures to assess intervention efforts is also limited, given the more targeted scope of behaviors found in diagnostic instruments such as the ADI-R (LeCouteur et al., 2003). Moreover, researchers have used instruments that assess similar behaviors relevant to ASD, though many of these tools were not designed specifically for the ASD population (and thus have issues with regard to comparing scores to a normative population) and are not truly appropriate for measuring changes in behavior (Brinkley et al., 2007; Lord et al., 2014). However, the Aberrant Behavior Checklist-Community (ABC-C; Aman & Singh, 2017) is one of the few tools that has been psychometrically examined to assess treatment outcomes for individuals with ASD, despite not being designed originally for the ASD population (Lord et al., 2014).

In their review, Bolte and Diehl (2013) determined that the ABC-C, the instrument of interest in this study, was the most-often used outcome instrument in ASD intervention research. It has been implemented in nearly 5% of all ASD intervention studies (Bolte & Diehl, 2013). By

category, the ABC-C was the most used instrument to measure changes in ASD pharmacological studies (10.1% of all studies) as well as in ASD alternative medicine studies (4.7% of all studies; Bolte & Diehl, 2013). Bolte and Diehl (2013) also found that the ABC-C was the most used measure to analyze hyperactivity symptomology and was implemented in 56.5% of all ASD intervention studies where hyperactivity was assessed as an outcome. Thus, despite the challenges with measuring ASD intervention outcomes and the great variety of instruments researchers have used, the ABC-C has emerged as one of the more popular and useful measures. Therefore, it is critical to thoroughly validate the ABC-C as a potential high quality instrument for ASD symptom monitoring.

The ABC-C as an ASD monitoring instrument. The ABC-C, although not designed specifically for individuals with ASD, has become very popular in ASD intervention research (Bolte & Diehl, 2013), including in both pharmacological and behavior studies (e.g., Hassiotis et al., 2009; Loebel et al., 2016). This is because both core and associated features of ASD are represented in the five subscales of the ABC-C: *Irritability, Hyperactivity, Social Withdrawal, Stereotypic Behavior,* and *Inappropriate Speech.* The following section will focus on some of those features of the ABC-C, although it is important to note that this is far from exhaustive and that the range of behaviors and all their potential effects is well beyond the scope of this brief overview.

***Irritability*.** Irritability and severe mood problems are common in individuals with ASD (Simonoff et al. 2012); however, there has not been much research on the causes of irritability (Mikita et al. 2015). Further, according to Mikita et al. (2015), the very definition of irritability is often inconsistent. As Mikita et al. (2015) explained, in research on individuals with ASD, irritability often refers to particular externalized behaviors such as verbal and physical

aggression, self-injurious behavior, and even destruction of property; while in research with neurotypical children, irritability often refers to mood presentations that do not always result in aggressive behaviors. In fact, as Mikita et al. (2015) pointed out, the ABC (and ABC-C), Irritability subscale includes many of the aforementioned externalized behaviors (e.g., self-injurious behavior, verbal and physical aggression). Yet, as Stringaris (2011) argued, irritability can manifest in mood states as well as in aggressive behaviors, but the drivers of those behaviors could be dissimilar. For instance, with regard to self-injurious behavior, prevalence is estimated to be around 30% of individuals with ASD, more prevalent than in individuals with other developmental disabilities (Soke et al., 2016). In addition, as Minshawi et al. (2014) indicated, self-injurious behavior can manifest for biomedical, genetic, and even behavioral reasons. Oliver and Richards (2015) highlighted research that argued that self-injury may occur as a result of operant learning, pain and discomfort, and even from a potential movement disorder. They emphasized that self-injury in ASD is often correlated with ID, with prevalence rates estimated between 33%-71% (Oliver & Richards, 2015). Overall, despite the complicated nature of the irritability construct, it is clear that irritability is thought to have influence on the behaviors of many individuals with ASD. Medications such as Risperidone and Aripiprazole are prescribed to help mitigate self-injury (Mahatmya, Zobel, & Valdovinos, 2008; Stachnik & Gabay, 2010), and the ABC-C Irritability subscale has been instrumental in research demonstrating the efficacy of pharmacological intervention (Aman & Singh, 2017).

Social Withdrawal. Part of the core diagnostic criteria in ASD concerns deficits in social communication and interaction (APA, 2013). These deficits, which are found in individuals with ASD regardless of cognitive abilities and often throughout the lifespan (Davis & Carter, 2014), include a lack of social-emotional reciprocity (e.g., limited sharing of thoughts and feelings, lack

of initiation or response in social interaction), lack of eye contact, and difficulty in relationship building (e.g., challenges in making friends and lack of interest in others; APA, 2013). There can also be symptoms of "catatonic-like motor behavior . . . mutism, posturing, grimacing, and waxy flexibility" (APA, 2013, p. 55). In addition, individuals with ASD can also maintain both high and low responsiveness to sensory stimuli (e.g., textures, sounds, tastes, smells, sights). Thus, ASD symptoms can present as sometimes withdrawn or lethargic behaviors.

Researchers have explored the relations of these core social deficits of ASD with their resulting internalized and externalized behavioral presentations. For instance, in a review of depression in children with ASD, Magnuson and Constantino (2011) argued that depression in ASD is often difficult to assess given the varied social-communication and cognitive deficits common to individuals with the disorder. They maintained that there can appear to be an overlap of symptomology or that ASD symptoms can mask a potential comorbid disorder. The authors stressed that difficulties with social situations and regulating emotions can also lead to internalizing challenges. They asserted that individuals with ASD requiring less substantial supports are often more susceptible to depression and anxiety as well and that signs such as mood lability, catatonia, hyperactivity, self-injurious behavior, and aggression can all be potential signs of depression. This is worthy of attention given the fact that these various symptoms are often found in items across the factors of the ABC-C. There may also be an increased risk for symptoms of depression and withdrawal in toddlers with ASD with high or low sensory thresholds, according to a study by Ben-Sasson et al. (2008). Thus, the signs and symptoms of social withdrawal and lethargy are complex in ASD and research is needed to better understand and detect them.

Stereotypic Behavior. Stereotypic behavior in the ABC-C specifically refers to motor stereotypic behaviors, which are considered to be core diagnostic features of ASD manifested as expressions of restricted, repetitive behaviors (APA, 2013). Motor stereotypic behavior is defined as repetitive motor and oral replies that offer no clear adaptive purpose (MacDonald et al., 2007). These behaviors include "repetitive, rhythmic, often bilateral movements with a fixed pattern (e.g., hand flapping, waving, or rotating) and regular frequency" (Péter, Oliphant, & Fernandez, 2017, p. 1). Interestingly, stereotypic behaviors are not uncommon in typically developing children as well; however, if they persist after age two with intensity and regularity, and also negatively affect daily functioning, they are often cause for concern (Chebli, Martin, & Lanovaz, 2016). With regard to affecting daily functioning, stereotypic behavior can hinder skill development and social relationships (Chebli, et al., 2016; Goldman et al. 2009). The etiology of stereotypic behaviors is unclear. Some suggest that the behaviors are psychological in origin and performed in accordance with behavioral functions such as self-gratification or escape (e.g., Goldman et al., 2009), while others believe there are biologically driven causes (Péter et al., 2017).

Chebli et al. (2016) showed that the vast majority of individuals with developmental disabilities, including both children and adults, perform at least one type of stereotypic behavior such as whole body movements, head, hand/finger, locomotion, sensory, vocal, or object manipulation behaviors. More specifically, the authors found prevalence rates for stereotypic behaviors of 88% in individuals with ASD compared to 61% among other developmental disabilities. Specific stereotypic movement types are more common than others, for example, sensory stereotypies are most often observed (73%), while head stereotypies are least common (30%; Chebli et al., 2016). Similarly, in a study by Goldman et al. (2009), it was found that

children with autism requiring substantial and less substantial supports had the highest percentage of stereotypic behaviors (70.6% and 63.6%) compared to children who had developmental language disorders (18.3%) and low IQ (30.9%) in the absence of autism. Goldman et al. (2009) also discovered that stereotypic behavior was strongly associated with autism, regardless of IQ; however, lower IQ did increase the amount and array of stereotypies.

Inappropriate Speech. One of the core diagnostic criteria for individuals with ASD involves deficits in communication and social interaction (APA, 2013). These deficits can include expressive and receptive language impairments such as severe language delays, poor speech comprehension, echolalia, affected (i.e., stilted and unusual intonation) and hyper-literal communication, repetitive speech, or idiosyncratic speech (APA, 2013). They can also involve deficits in conversational speech as well, such as poor social reciprocity and highly one-sided conversations. Of note, there can be similarities in communication deficits between individuals with ASD and ID (APA, 2013). However, a differential diagnosis is made between ASD and ID wherein within ASD an individual can have a distinct incongruity between social communication skills and interaction competencies compared to the individual's developmental level and nonverbal skills (APA, 2013). Ultimately, challenges with social and communication skills in individuals with ASD have been linked to increases in loneliness, social isolation and rejection, poorer academic and professional achievement, as well as mood challenges (White, Keonig, & Scahill, 2007).

Hyperactivity. A major revision in the DSM-5 (APA, 2013) from the DSM-IV-TR (APA, 2000) included changing ADHD from a rule out for ASD to recognizing it as a common comorbid disorder. In fact, a review of ADHD and ASD comorbidity by Matson, Rieske, and Williams (2013) found prevalence rate estimates of ADHD within the context of ASD to be

between 20% and 70%. In comparison, rates of individuals with ID and ADHD is estimated to be around 15%, although there is less confidence in that approximation given some of the symptom overlap between ADHD and ID (Araten-Bergman, 2015). Further, a study by Sprenger et al. (2013) showed that individuals with comorbid ASD and ADHD exhibited significantly more intense ASD symptomology, as measured on both the German versions of the ADI-R (Bölte, Rühl, Schmötzer, & Poustka, 2006, as cited in Sprenger et al., 2013) and the Social Responsiveness Scale (Bölte, Poustka, & Constantino, 2008, as cited in Sprenger et al., 2013). As such, although hyperactivity itself is not a core feature of ASD, its presence is common enough in individuals with ASD that it can affect a range of abilities such as language and communication, adaptive behavior, social skills, motor skills and also negatively influence challenging behavior, and executive functioning (Mannion & Leader, 2014). Symptoms of hyperactivity in individuals with ASD are often severe enough that they are commonly treated with various medications (Mire, Nowell, Kubiszyn, & Goin-Kochel, 2014) and behavioral interventions (Davis & Kollins, 2012).

Overall, the alignment of the ABC-C with the various core and associated features of ASD makes it a potentially important rating scale. Given the current need for quality ASD intervention outcome instruments (Lord et al., 2005), the ability of the ABC-C to measure behavioral change over time is particularly valuable. However, because the ABC-C was not developed specifically for individuals with ASD, a robust examination of its data structure is necessary to determine whether the scale is appropriately measuring what it purports to measure for the ASD population. To do this, factor analyses are performed, which examine the relations between individual items in a scale in order to uncover latent factors that reflect the scale's underlying constructs (Osborne & Banjanovic, 2016).

How Rating Scales Derive Factors

Factor analysis has become one of the most frequently used methods to both develop and evaluate the psychometric properties of psychological instruments (Floyd & Widaman, 1995). Factor analytic techniques were developed because of the inherent complexity in discerning patterns and relationships in sets of data (Fabrigar & Wegener, 2012). Common factors comprise these relationships via specific correlational patterns. Such factors are attributed to constructs underlying the items in a measure. Factor analytic techniques are used to determine the number and types of factors inherent in a measurement scale, which helps provide researchers and clinicians with information about the measurement attributes of an instrument. This information is given in the form of estimates regarding the strength and direction of influence each of the individual factors places on each of the items (Fabrigar & Wegener, 2012). These estimates are referred to as *factor loadings* (Fabrigar & Wegener, 2012). Two core factor analytic methods are employed to discern the nature of these factor loadings: Exploratory Factor Analysis (EFA) and Confirmatory factor analysis (CFA; Fabrigar & Wegener, 2012).

Exploratory factor analysis and principal component analysis. EFA is used to discern the factor structure in a data set, i.e., a way to detect the number and type of latent factors that account for data covariation (O'Rourke & Hatcher, 2013). EFA is similar to Principal Components Analysis (PCA) in that both are methods used to condense the number of variables in a data set. Although PCA and EFA both aim to derive the supposed underlying constructs inherent in a set of variables, they critically differ in how those factors are statistically derived and in the theoretical direction of influence between factors and indicators.

In PCA, derived components (or factors) are made up of linear combinations of observed variables with each variable contributing a different weight or percentage to the components

(O'Rourke & Hatcher, 2013; Osborne & Banjanovic, 2016). PCA maintains the assumption that all observed variables are measured without error, meaning it elicits a total variance, subsuming common variance, unique variance, and random error variance in its solutions (Pedhazur & Schmelkin, 1991). As a result, a PCA analysis could result in overestimated levels of variance in the variables of the derived factors (Gorsuch, 1997; Osborne & Banjanovic, 2016).

On the other hand in EFA, observed variables function as linear combinations of the latent factors (O'Rourke & Hatcher, 2013). Unlike PCA, EFA solutions account for shared or common variance only. EFA also accounts for both unique and error variance in the overall model (O'Rourke & Hatcher, 2013; Osborne & Banjanovic, 2016).

In general, EFA is considered to be most useful in uncovering the latent constructs within data (Osborne & Banjanovic, 2016). However, EFA is best employed when a researcher maintains few to no strong assumptions about the nature of the relationships in a dataset and is known as an "*unrestricted factor analysis*" (Fabrigar & Wegener, 2012, p. 4). It is a data-based approach that, as Long (1983) explained, enables a researcher to generate a wide range of possible solutions with a dataset given the lack of "substantively meaningful constraints" (p. 12). Once hypothesized factor models (based on theory or prior data-based results) are available, then Confirmatory factor analysis (CFA) is typically used to assess the fit of such models.

Confirmatory factor analysis. CFA is used to test a theorized factor structure, often derived from a previously performed EFA (Fabrigar & Wegener, 2012). As a "*restricted factor analysis*" (Fabrigar & Wegener, 2012, p. 4) it imposes specific constraints on the data, thereby limiting the number of possible solutions (Long, 1983). This method is used to substantiate or refute particular hypothesized factor structures (Pett, Lackey, Sullivan, 2003).

Unlike with EFA, a CFA provides a researcher the ability to apply more detailed restraints on the data to determine the structure of a hypothesized model (Byrne, 2005). For instance in an EFA, factors are either all correlated or independent, whereas in a CFA the researcher can indicate which correlations she believes are meaningfully related as well as the extent of those relationships (Byrne, 2005; Pedhazur & Schmelkin, 1991). In CFA a researcher can indicate which items load on which particular factors, whereas in EFA, all items, at differing levels of strength, load on every factor (Pedhazur & Schmelkin, 1991). This level of flexibility in CFA even provides researchers the ability to correlate different item errors, unlike in EFA where item errors are always uncorrelated (Pedhazur & Schmelkin, 1991). Overall, the differences between EFA and CFA ultimately enable them to be complimentary in factor analytic studies.

EFA and CFA as complements. As Gerbing and Hamilton (1996) demonstrated, EFA and CFA are complimentary in that EFA is highly effective as a first step in discovering a latent factor structure in a model, whereby CFA can then be used to evaluate the strength of that model. As Fabrigar, Wegener, MacCallum, and Strahan (1999) argued, EFA is a more logical method to use compared to a CFA when there is a lack of data or a weak empirical foundation to make robust assumptions about the number and nature of common factors. The authors contend that using a more restrained CFA approach without an EFA makes it highly likely that researchers will potentially not recognize the existence of other possible theoretical models. Further, as Church and Burke (1994) stated, reproducing a particular EFA structure with various samples offers strong evidence of the viability of that structure because that model has been generated repeatedly without any particular limiting parameters. Once there is a solid basis for identifying

a particular model, a CFA is the more appropriate method, thus making EFA and CFA particularly effective when used together (Fabrigar et al., 1999).

It is important to point out that historically EFAs in the developmental disability literature have often not been performed with the highest levels of rigor (Norris & Lecavalier, 2010b). Norris and Lecavalier (2010b) performed a study on EFAs from 1997 to 2008 amongst five of the most popular journals for developmental disabilities. Looking at 66 different studies, the authors found that 66% of studies used PCA instead of EFA (35%), 59% used orthogonal rotations instead of oblique rotations (33%), and with regard to factor retention criteria— although most reported the use of multiple methods— clinical meaningfulness (82%) was the most popular followed by the use of the eigenvalues > 1 criteria (76%), scree plots (56%), parallel analysis (4%), and Velicer's MAP test (2%). These findings reflect a contrast to the expert recommendations made by Norris and Lecavalier (2010b), including using EFA instead of PCA, and using oblique instead of orthogonal rotations. Overall, Norris and Lecavalier (2010b) highlight the fact that EFAs in the developmental disability literature have often not been performed according to best practices. This is also evident when analyzing many of the factor analyses performed on the Aberrant Behavior Checklist (ABC; Aman, Singh, Stewart, & Field, 1985a and the Aberrant Behavior Checklist-Community (ABC-C; Aman & Singh, 2017).

Factor Analyses in the Development of the ABC-C

From the initial development of the ABC (Aman et al., 1985a) to its current version, the ABC-C (Aman & Singh, 2017) has undergone many factor analyses. These analyses have varied with regard to their level of rigor. Across the different iterations of the scale, the numerous factor analyses have resulted in solutions that have both confirmed and differed from the authors' derived structures. In particular, with regard to the three factor analyses of the ABC-C

performed specifically with the ASD population, there have been distinct inconsistencies, raising important questions. The following section will provide a brief historical overview of each of the different iterations of the ABC-C along with the important findings from the related factor analytic studies. Further, a more intensive examination of the three particular factor analyses of the ABC-C with ASD samples will be provided.

The ABC. The original development of the scale by Aman et al. (1985a) resulted in a five-factor solution (I = Irritability, Agitation, Crying; II = Lethargy, Social Withdrawal; III = Stereotypic Behavior; IV = Hyperactivity, Noncompliance; V = Inappropriate Speech) using a PCA (M. Aman, personal communication, February 2, 2018), chosen through an eigenvalue criterion and author judgment, and included examining multiple factor solutions (i.e., three- to seven- factor solutions). The PCA was conducted using a sample of adults with intellectual disabilities who were rated by institutional staff members. According to the authors, solutions that included fewer factors resulted in subscales that were too wide-ranging while solutions that included more than five factors resulted in suspected overlapping constructs. Subsequent factor analyses of the ABC (Aman & Singh, 1986) with similar samples of individuals with intellectual disabilities (e.g., Aman, Richmond, Stewart, Bell & Kissel, 1987; Bihm & Poindexter, 1991; Freund & Reiss, 1991, Newton & Sturmey, 1988; Rojahn & Helsel, 1991) generally did not examine multiple factor solutions—but focused only on the degree to which a five-factor solution matched expectations. This means that the five-factor structure derived by Aman et al. (1985a) appeared to be what most authors expected to find a priori. As a result, additional alterative factor structures were not thoroughly explored (see Table 4 for details).

Table 4. *Summary of Exploratory Factor Analyses of the Aberrant Behavior Checklist (ABC)*

Research Study	Source	N	Sample	Rater	Factor Analysis Method/Factor Retention Process	Factor Solution(s) Examined	Chosen Factor Solution/ Names	% of Variance Explained by Factor Solution
Aman, Richmond, Stewart, Bell, & Kissel (1987)	Residential facility	531	Male: 61% Moderate ID: 7 % Severe ID: 27% Profound ID 67% Deaf: 6% Epilepsy 35% CP: 13 % Psychosis: 8% Mean age: 33.5 All ambulent British sample	Residential staff	Principle Axis Factoring with Varimax & Promax rotations/ Predetermined	5-factor	<u>5-factor</u> I: Irritability, Agitation Crying II: Lethargy, Social Withdrawal III: Stereotypic Behavior IV: Hyperactivity , Non-Compliance V: Inappropriate Speech	n/a
Newton & Sturmey (1988)	Residential facility	209	Female: 43% All individuals ID 45% Non-ambulent, Mean age: not provided	Residential staff	Principle Axis Factoring with Varimax & Promax rotations/ Predetermined	5-factor	<u>5-factor</u> Not named, authors reported that factors best "corresponded to" the following: I: Lethargy, Social Withdrawal) II: Irritability, Agitation, Crying III: Hyperactivity, Non-compliance IV: Inappropriate Speech V: Stereotyped Behavior	55.1%

Table 4 (cont'd)

Bihm & Poindexter (1991)	Residential facility	470	53% Male Profound ID: 72% Severe ID: 21% Moderate: 7% Mean age: 27 27% Non-ambulent	Residential Staff	Principal Axis Factoring with Varimax rotation/ Predetermined	5-factor	<u>5-factor</u> I: Irritability, Agitation Crying II: Lethargy, Social Withdrawal III: Stereotypic Behavior IV: Hyperactivity , Non-Compliance V: Inappropriate Speech	n/a
Freund & Reiss (1991) [a b]	Center for individuals with disabilities	110	69% male Mean IQ: 54 Borderline ID: 14% Mild ID: 37% Moderate ID: 25% Severe ID: 24% Mean age: 11	Parents	Principal Axis Factoring with Varimax & Promax rotations/ Scree test	5-factor	<u>5-factor</u> I: Irritability II: Withdrawal III: Hyperactivity IV: Stereotypies V: Inappropriate Speech	55%
Freund & Reiss (1991) [b]	Center for individuals with disabilities	94	69% Male Mean IQ: 52 Mean age: 11	Teachers	Principal Axis Factoring with Varimax & Promax rotations/ Scree test	5-factor	<u>5-factor</u> I: Irritability II: Withdrawal III: Hyperactivity IV: Stereotypies V: Inappropriate Speech	60%

Table 4 (cont'd)

Rojahn & Helsel (1991)	Inpatient psychiatric unit	199	77% Male 92% With ID 8% Untestable Mild ID: 29% Moderate ID: 30% Severe ID: 17% Profound ID:10% Mean age: 8	Staff	Principal Axis Factoring with Varimax & Promax rotations/ Predetermined	5-factor	<u>5-factor</u> I: Irritability II: Lethargy/Social Withdrawal III: Stereotypic Behavior IV: Hyperactivity V: Inappropriate Speech	32%

[a] Four items were also excluded in the factor analysis because of loadings below .30 on all 5 factors.
[b] Modified version of the ABC items and the descriptors for "clarity and reduced reading level" (p.439). Descriptors from the ABC manual were reworded for each questionnaire form and added to each question.

Also of note, in the factor analysis by Freund and Reiss (1991), the authors developed two versions of the scale (a parent-ABC and a teacher-ABC) and incorporated different altered item descriptors for each version to the rating form derived from item descriptions found in the original ABC manual (Aman & Singh, 1986). This could be perceived as a fundamental change in the items and result in differences in the way that participants understand the items without altered descriptors, making it problematic to compare the results of this augmented form of the ABC (Freund & Reiss, 1991) to the original ABC (Aman & Singh, 1986). Unfortunately, this was the only study of the original ABC that included teachers and parents as raters, rather than direct care staff.

The ABC-C. According to Aman and Singh (1994), revision of the original ABC was necessary given the fact that deinstitutionalization had become much more commonplace. As such, Marshburn and Aman (1992) performed an EFA of the original ABC with the intent of seeing how robust it would be when used outside of an institutional setting, and instead within the community (i.e., special education classrooms), rated by teachers. To do this, Marshburn and Aman (1992) altered the wording of various items to make the scale more appropriate for this different population. In a subsequent analysis by Aman, Burrow, and Wolford (1995), item wordings were further revised and the scale was then tested with a sample of individuals (n = 1,024) living in group homes, rated by the staff. As a result a *community* version of the ABC was created (i.e., the ABC-C; Aman & Singh, 1994). This involved changing both instructions on protocols and the wording of items to reflect an instrument flexible enough to be used in various environments. In total, 17 of the 58 items on the scale were altered from the original ABC (see Table 5 for details).

Table 5. *Item Changes Between the ABC and ABC-C*

Item Number	ABC[a] Item	ABC-C[b] Item
1	Excessively active on ward	Excessively active at home, school, work, or elsewhere
2	Injures self	Injures self on purpose
4	Aggressive to other patients and staff	Aggressive to other children or adults (verbally or physically)
7	Boisterous	Boisterous (inappropriately noisy and rough)
10	Temper tantrums	Temper tantrums/outbursts
11	Stereotyped, repetitive movements	Stereotyped behavior; abnormal, repetitive movements
13	Impulsive. Acts without thinking	Impulsive (acts without thinking)
14	Irritable	Irritable and whiny
16	Withdrawn	Withdrawn; prefers solitary activities
20	Fixed facial expression; lacks emotional reactivity	Fixed facial expression; lacks emotional responsiveness
27	Moves or rolls head back and forth	Moves or rolls head back and forth repetitively
37	Unresponsive to ward activities (does not react).	Unresponsive to structured activities (does not react)
38	Does not stay in seat during lesson period	Does not stay in seat (e.g., during lesson or learning periods, meals, etc.)
40	Is difficult to reach or contact	Is difficult to reach, contact, or get through to
47	Stamps feet while banging objects or slamming doors	Stamps feet or bangs objects or slams doors
49	Rocks body back and forth	Rocks body back and forth repeatedly
57	Throws temper tantrums when he/she does not get own way	Has temper outbursts or tantrums when he/she does not get own way

[a] Items from the original ABC (Aman & Singh, 1986)
[b] Items from the ABC-C (Aman & Singh, 1994)

Aman and Singh (1994) acknowledged that making these changes could have led to a different factor structure. However, they insisted that the subsequently published contemporary studies of the altered scale showed that the community version maintained the original five-factor structure. This argument made by Aman and Singh (1994) is perplexing given that the first iteration of the ABC-C, in the study by Marshburn and Aman (1992), with subjects aged six to 21 years (M = 12.5) who were rated by teachers in special education classrooms, resulted in a four-factor solution, excluding the *Inappropriate Speech* factor from the original ABC (Aman & Singh, 1986). In the subsequent analysis by Aman et al. (1995), which further iterated on the item wording changes made in Marshburn and Aman (1992), only the original five-factor solution was considered for this study without testing the four-factor solution identified with the younger population. Results of this analysis led the test authors to conclude that the newly revised wording on the scale did not alter the five-factor structure from the original ABC (Aman & Singh, 1994). Aman et al. (1995) also found that 95% of the items loaded as on the original ABC factors. They argued that that the new ABC-C version was valid for rating adults with intellectual disabilities residing in the community.

Further, Aman and Singh (1994) provided updated reference group data, based upon the Aman et al. (1995) and Marshburn and Aman (1992) studies. Reference group data were available for teacher ratings of children in special education, ages six to 21 years (M = 12.5) and health professional ratings of adults in group homes, ages 18 to 89 years (M = 42.46, SD = 14.2), both using the same five-factor solution despite finding a four-factor solution for youngsters. The authors also clarified that the scale was not just intended for adults, but children and adolescents as well. The original scale's name was modified to the ABC-Residential (ABC-R) and the new scale was referred to the ABC-Community (ABC-C).

A follow up study of the ABC-C by Brown, Aman, and Havercamp (2002) examined a four-and five-factor solution to further to assess the factor structure of the ABC-C for children and adolescents in special education as rated by their parents. Using the scree plot method (Cattell, 1966) and the eigenvalue > 1 criterion (Guttman, 1954; Kaiser, 1960) to determine the likely number of factors, Brown et al. (2002) chose a four-factor solution (I = Irritable, Uncooperative; II = Lethargy/Withdrawal; III = Hyperactivity; IV = Stereotypy, Self-Injury), excluding the Inappropriate Speech factor found on the ABC-C. However, Brown et al. (2002) argued that coefficients of congruence used to compare the overlap between their chosen four-factor solution on the ABC-C and the original ABC ranged from moderate to high (Irritability = .85; Lethargy/Withdrawal = .91; Stereotypic Behavior = .62; Hyperactivity/Noncompliance = .85). As such, the authors reasoned that despite their own differing results, the original item assignment (and factor structure) from the ABC should be maintained. Brown et al. (2002) asserted that prior factor analyses performed with children and adolescents (e.g., Freund & Reiss, 1991; Marshburn & Aman 1992; Rojahn & Helsel, 1991) had been "remarkably consistent" with the original ABC factor structure (p. 51). This is a perplexing argument given that Freund and Reiss (1991) and Rojahn and Helsel (1991) both pre-specified and examined only a five-factor structure in their analyses and Marshburn and Aman (1992) arrived at a four-factor solution. Brown et al. (2002) also argued that a different scoring system would only be necessary if there was strong evidence that a factor structure was different for a particular population, which they claimed was not appropriate in this case. Brown et al. (2002) also performed a CFA to further examine their EFA results with the original ABC factor structure and found a modest fit with an RMSEA of .088. Further, attempting to justify their decision, Brown et al. (2002) reported that overlap with their current solution and the original ABC showed strong internal consistency with

regard to item assignment (Irritability = .91; Lethargy/Withdrawal = .90; Stereotypic Behavior = .84; Hyperactivity = .95; Inappropriate Speech = .77), with 41 out of 58 items loading the same way or 71% congruent over all (Brown et al., 2002; Aman & Singh, 2017).

A variety of other factor analyses (EFAs and CFAs) of the ABC-C with ID and alternative populations were also performed. For instance, two other examples of studies that used EFAs with ID samples include Ono (1996), who developed a Japanese translation of the ABC-C, and Zeilinger, Weber, and Haveman (2011) who developed a German version of the ABC-C (See Table 6 for a summary of EFAs of the ABC-C with ID and alternative populations).

Table 6. *Summary of Exploratory Factor Analyses of the Aberrant Behavior Checklist-Community (ABC-C) with ID and Alternative Populations*

Research Study	Source	*N*	Sample	Rater	Factor Analysis Method/Factor Retention Process	Factor Solutions Examined	Chosen Factor Solution/Names	% of Variance Explained by Factor Solution
Marshburn & Aman (1992)[a]	Special education classrooms	666	64% with IQ < 80 and deficits in adaptive behavior, 27% with multiple handicaps, 5% with IQ < 70 and severe handicaps, 5% from unspecified special education classes, Mean age: 13	Teachers	Principal Axis Factoring with Promax rotation/ Scree test	4-factor 5-factor 6-factor	<u>4-factor</u> I: Hyperactivity II: Irritability III: Lethargy, Social Withdrawal IV: Stereotypic Behavior	52%
Aman, Burrow, & Wolford (1995)	Group homes	1024	59% male Mild ID: 3% Moderate ID: 17% Severe ID: 25 % Profound ID: 44% Mean age: 43	Staff	Principle Axis Factoring with Varimax & Direct Oblimin rotations/ Predetermined	5-factor	<u>5-factor</u> I: Hyperactivity/Non-Compliance II: Lethargy/Withdrawal III: Stereotypic Behavior IV: Irritability V: Inappropriate Speech	55%
Ono (1996) [b]	Residential institutions	322	Profound ID: 22% Severe ID: 48% Moderate ID: 30% Mean age: 30	Staff	Principal Axis Factoring with Oblique rotation/ Predetermined	5-factor	<u>5-factor</u> I: Hyperactivity, Noncompliance II: Lethargy III: Stereotypy IV: Inappropriate Speech V: Irritability	n/a

Table 6 (cont'd)

Brown, Aman, & Havercamp (2002)[c]	Special education classes	601	56% male Mean age: 13 51% with IQ ≤ 80 and adaptive behavior issues, 22% with developmental disabilities	Parents	Principle Axis Factoring with Promax rotation/ Scree test	4-factor 5-factor	<u>4-factor</u> I: Irritable, Uncooperative II: Lethargy/Withdrawal III: Hyperactivity IV: Stereotypy, Self-Injury	48%
Zeilinger, Weber, Haveman (2011)[d]	Various individuals in the community	270	All with ID, Mild or Moderate ID: 77% Severe or Profound ID: 23% Mean age: 40	Caregivers	Principal Component Analysis with Oblique rotation/ Parallel analysis	5-factor	<u>5-factor</u> 1: Hyperactivity II: Lethargy III: Stereotypic Behavior IV: Inappropriate Speech V: Irritability	51%
Sansone et al. (2012)[e]	Fragile X treatment and research centers	315	All with Fragile X syndrome, Mean age: 11 Males: 73% Mean IQ: 58	Caregivers	EFA using Ordinary Least Squares estimation with Promax rotation/ Scree test, Parallel analysis	5-factor 6-factor 7-factor	<u>6-factor</u> I: Irritability II: Hyperactivity III: Socially Unresponsive/Lethargic IV: Social Avoidance V: Stereotypy VI: Inappropriate Speech	n/a

[a] = Authors report modifications made to item wordings on the ABC to make the scale appropriate for use with children in the community.
[b] = Japanese translation of the ABC-C
[c] = A CFA was also run in this study.
[d] = German translation of the ABC-C
[e] = Item parceling was used to condense the three self-injurious behavior items. A CFA was also run in this study.

Studies employing CFAs include Lehotkay et al. (2015), who developed an Indian translation of the ABC-C in Telugu; Sansone et al. (2012, who also used an EFA) and Wheeler et al. (2014) who both explored the factor structure of the ABC-C with Fragile-X Syndrome samples; and Schmidt, Huete, Fodstad, Chin, and Kurtz (2013) who sampled a small population of children under age five (n = 97), with a sample age mean of 2.79 years that Aman and Singh (2017) claimed had not been an adequately validated age range for the ABC-C (see Table 7 for a summary of all CFAs of the ABC-C with ID and alternative populations). Each of these aforementioned analyses have merit with regard to examining the utility of the ABC-C with various populations; however, given their samples' inherent differences, these studies are not similar (or comprehensive enough in many cases) to use as evidence to either support or refute the ABC-C factor structure currently promoted by the test authors.

Table 7. *Summary of Confirmatory Factor Analyses of the Aberrant Behavior Checklist-Community (ABC-C) with ID and Alternative Populations*

Research Study	Source	*N*	Sample	Rater	Cross Validation Sample Used	Factor Solutions Examined	Factor Solution Chosen	Parameter Metrics Cited
Brown et al. (2002)[a]	Special education classrooms	601	56% male Mean age: 13	Parents	No	Aman et al. (1985) 5-factor	5-factor	RMSEA = .088
Sansone et al. (2012)	Fragile X treatment and research centers	315	All with Fragile X syndrome, Mean age: 11 Males: 73% Mean IQ: 58	Caregivers	Yes	Sansone et al. (2012) 1-factor, Sansone et al. (2012) 5-factor, Sansone et al. (2012) 6-factor	6-factor + 3 item Self-injury item parcel	RMSEA: .045 TLI: .98 SRMR: .03 SB χ^2: < .001
Schmidt et al. (2013)	Hospital outpatient clinc & home-based research study	97	Males: 73% DD or ID: 45% ASD: 13% Mean age: 3	Caregivers	No	Aman & Singh (1994) 5-factor	5-factor	RMSEA: .12 CFI: .55 χ^2/df: 2.36
Wheeler et al. (2014)	Research registry	292	All with Fragile X syndrome, Mean age: 20 Males: 100%	Families	No	Aman & Singh (1994) 5-factor, Sansone et al. (2012) 6-factor	6-factor	CFI: .94 TLI: .93 RMSEA: .05

RMSEA= Root Mean Square Error of Approximation, *TLI* = Tucker Lewis Index, *SRMR* =Standard Root Mean Square Residual, *SB* χ^2 = Satorra-Bentler Chi Square, χ^2/df = Chi Square/degrees of freedom, *CFI* = Comparative Fit Index

[a] A CFA was also conducted using an EFA of the ABC-C that was scored with a dichotomous rating, meaning the presence or absence of a particular symptom. Because this represents a major change to the scoring of the scale, this was not included in this table.

The ABC-C, second edition. Aman and Singh (2017) made clear that the ABC-C, Second Edition (ABC-C2) is not in fact a second edition of the scale, but rather a second edition of the *manual*. However, some slight changes were made to the instrument. Scale items all remained the same, but some subscale names were slightly modified (see Table 8 for details).

Table 8. *Subscale Name Changes in the ABC-C Second Edition Manual*

ABC-C Subscale Name[a]	ABC-C Subscale Name (Second Edition Manual)[b]
Irritability, Agitation, Crying	Irritability
Lethargy, Social Withdrawal	Social Withdrawal
Stereotypic Behavior	Stereotypic Behavior
Hyperactivity, Noncompliance	Hyperactivity/Noncompliance
Inappropriate Speech	Inappropriate Speech

[a] Subscale names from the ABC-C (Aman & Singh, 1994)
[b] Subscale names from the ABC-C, Second Edition manual (Aman & Singh, 2017)

Changes in subscale naming include truncating the Irritability, Agitation, Crying subscale to just Irritability, replacing the comma in the Hyperactivity, Noncompliance subscale with a virgule to read as Hyperactivity/Noncompliance; and changing the Lethargy, Social Withdrawal subscale to Social Withdrawal. No specific explanation or justification was provided in the manual for the name changes.

The recent changes to the ABC-C factor names in the ABC-C2 manual seem to be minor, except perhaps for the change from the Lethargy, Social Withdrawal factor to just Social Withdrawal. This change signals either a removal of the shared importance of the Lethargy construct from the factor or subsumes it under the Social Withdrawal conceptual umbrella. Either way, the change could be conceptually and clinically significant with regard to other populations, including the ASD population.

Summary of the factor analyses of the ABC-C for the ID population. Despite the fact that there have been numerous factor analyses of the ABC-C for the ID population—both EFAs and CFAs—it is difficult to make definitive conclusions regarding the robustness of the five-factor model (see Table 6 and Table 7 for details). Of the three EFAs with the ABC-C that had been performed with ID populations (not including the Fragile-X populations or those studies that were intended as instrument language translations) two resulted in a four-factor model solution (Brown et al., 2002; Marshburn & Aman, 1992) and one resulted in a five-factor model solution (Aman, et al., 1995). Yet, in the Aman et al. (1995) study, no other factor structures were explored because the five-factor model was assumed to be the only model in need of testing. Additionally Marshburn and Aman (1992) and Brown et al. (2002) also chose samples of children from special education classrooms, while Aman et al. (1995) sampled individuals from group homes. All three also used different rater types (teachers, staff, and parents). The only CFA that had been performed from these studies came from Brown et al. (2002), which used the same sample in its EFA (i.e., the sample was not independent and also resulted in a four-factor solution). Only five-factors were specified in the model, which ultimately was not shown to be a reasonable fit with the data (RMSEA = .088). It is worth mentioning that the CFA from Schmidt et al. (2013) which analyzed a small mixed sample (n = 97) of children with ID or developmental disabilities, also resulted in a poor fit (RMSEA = .12) with the five-factor solution.

The Sansone et al. (2012) study, although using a Fragile-X population and not strictly an ID population, did explore multiple factor solutions and included a CFA that resulted in a six-factor solution that was shown to have a good model fit (RMSEA = .045, SRMR = .03, TLI = .98). Wheeler et al. (2014) also performed a CFA in their study of the Fragile-X population and

found a better fit (RMSEA = .05) with the six-factor model found in Sansone et al. (2012) compared to the Aman and Singh (1994) five-factor model.

Overall, based upon the numerous factor analyses that have been performed with the ID population with the ABC and ABC-C, there are legitimate questions that can be raised regarding the robustness of the five-factor model. A review of this historical literature appears to strengthen the need to further examine the factor structure of the ABC-C, particularly when it is used with an ASD population, as it may not be prudent to assume that the authors' chosen five-factor solution is definitively appropriate.

The ABC-C in the ASD population. At the time of this writing, three EFAs and two CFAs of the ABC-C have been performed specifically with an ASD sample (Brinkley et al., 2007; Kaat et al., 2014; Mirwis, 2011). Brinkley et al. (2007) arrived at a four-and a five-factor solution, Kaat et al. (2014) arrived at a five-factor solution, while Mirwis (2011) retained a seven-factor solution. Each of the studies used slightly different methods to perform their analyses. Brinkley et al. (2007) and Kaat et al. (2014) also ran CFAs to assess their model fit, though only Kaat et al. (2014) cross-validated their factor model in a separate sample. Table 9 includes a summary of EFAs of the ABC-C with ASD samples and Table 10 contains a summary of CFAs of the ABC-C with ASD samples.

Table 9. *Summary of Exploratory Factor Analyses of the Aberrant Behavior Checklist-Community (ABC-C) with ASD Samples*

Research Study	Source	*N*	Sample	Rater	Factor Retention Process	Factor Solutions Examined	Chosen Factor Solution/Names	% of Variance Explained by Factor Solution
Brinkley et al. (2007)	Recruited from the community	275	All with ASD, Mean age: 11 Intact Lang.: 73% VABS adaptive behavior composite: T =61 Males: 85%	Parents	Principal Component Analysis with Varimax & Promax rotations/ Eigenvalues > 1, Scree test	4-factor 5-factor	Both solutions retained <u>4-factor</u> I: Hyperactivity/ Noncompliance II: Lethargy/Social Withdrawal III: Stereotypy IV: Irritability <u>5-factor</u> I: Hyperactivity/ Noncompliance II: Lethargy/Social Withdrawal III: Stereotypy IV: Irritability V: Inappropriate Speech	4-factor (71%) 5-factor (76%)
Mirwis (2011)	Special education classes	236	All with ASD Mean age: 8.5 Mean IQ: 59 Males: 85%	Special Education /Agency Staff	Principal Axis Factoring with Promax rotation/ Eigenvalues > 1, Scree test, Parallel analysis	5-factor 6-factor 7-factor 8-factor	<u>7-factor</u> I: Irritability II: Hyperactivity III: Withdrawal IV: Lethargy V: Stereotyped Behaviors VI: Inappropriate Speech VII: Self-Injurious Behavior	86%

Table 9 (cont'd)

Kaat et al. (2014)	Children's hospitals (Autism Treatment Network)	1130	All with ASD Mean age: 6 Males: 84% IQ < 70: 47%	Parents	Principal Axis Factoring with Crawford-Ferguson Quartimax rotation/ Eigenvalues > 1, Scree test, Clinical meaningfulness	4-factor 5-factor 6-factor	<u>5-factor</u> I: Irritability II: Lethargy/Social Withdrawal III: Stereotypic Behavior IV: Hyperactivity/ Noncompliance V: Inappropriate Speech	n/a

Table 10. *Summary of Confirmatory Factor Analyses of the Aberrant Behavior Checklist-Community (ABC-C) with ASD Samples*

Research Study	Source	*N*	Sample	Rater	Cross Validation Sample Used	Factor Solutions Examined	Factor Solution Chosen	Parameter Metrics Cited
Brinkley et al. (2007)[a]	Recruited from community	275	All with ASD Mean age: 11 Intact language: 73% VABS adaptive behavior composite: T = 61 Males: 85%	Parents	No	Aman & Singh (1994)	5-factor	RMSEA: .091 NFI: .089 NNFI: .92

Table 10 (cont'd)

Kaat et al. (2014)	Children's hospitals (Autism Treatment Network)	763	All with ASD Mean age: 7 Males: 84% IQ < 70: 47%	Parents	Yes	Aman et al. (1985a) 5-factor, Brown et al. (2002) 4-factor, Brinkley et al. (2007) 4-factor, Brinkley et al. (2007) 5-factor, Sansone et al. (2012) 6-factor	5-factor	SB χ^2: statistically significant (exact *p-value* not reported) RMSEA: .085 SRMR: .10

RMSEA= Root Mean Square Error of Approximation, *NFI* = Normed Fit Index, *NNFI* = Non-Normed Fit Index, *SRMR* =Standard Root Mean Square Residual, *SB* χ^2 = Satorra-Bentler Chi Square,

[a] = A CFA was also conducted on N = 216 consisting of individuals with low self injury and N = 59 with high self-injury. Given that the sample was split for a specific analysis of self-injury, it was not included in this table

Brinkley et al. (2007). Brinkley et al. (2007) was the first study to assess the factor structure of the ABC-C with an ASD sample. The authors cited the lack of existing rigorous instruments to measure associated features of ASD and the importance of potentially using these features to help identify existing ASD subgroups—which in turn could indicate the existence of varying biological causes for the range of behaviors currently subsumed under the broad ASD diagnosis. Further, they stated that assessing the ABC-C factor structure for the ASD population could help to inform ASD treatment and further research.

To perform this analysis, Brinkley et al. (2007) sampled 275 individuals with ASD from three to 21 years old (M =10.6; SD = 4.4), with 79% of the sample white, 85% male, and 24% with impaired language (i.e., a 1 or 2 score on the ADI-R LeCouteur et al., [2003]). Subjects were recruited via advertisements, support groups, and from clinical and educational environments. Inclusion criteria were comprised of the aforementioned age range and a DSM-IV (APA, 1994) clinical diagnosis of ASD (i.e., autistic disorder, Asperger's disorder, and PDD-NOS, although this was not clearly articulated in the study and only referred to as ASD from a DSM-IV diagnosis). Individuals with severe physical or neurological disorders were excluded. Parents completed all ABC-C ratings.

A PCA was used as the factor analytic method with varimax (Kaiser, 1958) and promax (Hendrickson & White, 1964) rotations. To determine the number of factors to retain, the eigenvalue-greater-than-one criterion along with the scree test method were employed. A CFA was also used to assess the factor solution with the ABC-C structure to determine the quality of model fit. Results were not cross-validated with an independent sample. Four-and five-factor solutions were considered and a further stratification of groups was performed to explore the

factor structure of individuals with low and high self-injurious behavior characteristics—based on outcomes from the ABC-C.

Brinkley et al. (2007) presented two solutions, a five-factor solution, which accounted for 76% of the variation in the data and a four-factor solution which accounted for 71% of the variance in the data. The CFA for the five-factor solution yielded a root mean square error approximation (RMSEA) of .091, which placed the model fit in a range between reasonable ($\leq$ .08) and poor ($\geq$ .10; Brown & Cudeck, 1993 in Brinkley et al., 2007), and a normed fit index (NFI) of .089 and non-normed fit index (NNFI) of .92, showing moderate fit (Stevens, 2002 in Brinkley et al., 2007). In the five-factor solution, 96% of the variables on the Stereotypic Behavior, Inappropriate Speech, and Lethargy, Withdrawal factors loaded on the same factors as the ABC-C. The biggest difference between the ABC-C and the Brinkley et al. (2007) five-factor solution concerned the shifting of all the items from the Irritability, Agitation, Crying factor to the Hyperactivity, Noncompliance factor except for the three items which focused on self-injurious behavior. With the four-factor solution, the Inappropriate Speech factor was dropped and items were distributed between the Stereotypic Behavior and the Hyperactivity, Noncompliance factors. Also, similar to the five-factor solution, the four-factor solution maintained the Irritability scale but only with the same three items focused on self-injurious behavior.

To further explore the emergence of the Self-Injurious Behavior factor, Brinkley et al. (2007) separated out individuals with no or low self-injury profiles (based upon whether the sum of the three self-injury items added up to scores < 3) and medium or high self-injurious behavior profiles (based upon whether the sum of the three self-injury items added up to scores $\geq$ 3). The low-self injury group (N = 216) and the high-self injury group (N = 59) were then compared

across each of the different factors with data showing the high-self injury group scoring significantly higher on average across all of the original ABC-C scales except the Inappropriate Speech factor. Brinkley et al. (2007) then measured the factor structure differences between the two groups, despite the potentially small sample size (N = 50) of the high-self injury group. The authors found a five-factor solution similar to that of the ABC-C for the low self-injury group, though they did not find any significant loadings (all $\leq$ .2) for any of the self-injurious behavior items. The RMSEA was a .088 indicating a model fit ranging between reasonable and poor (Brown & Cudeck, 1993 in Brinkley et al., 2007) and an NFI and NNFI of .85 and .90 suggesting a borderline fit (Brinkley et al., 2007). For the high-self injury group a five-factor solution was also found however all of the self-injurious behavior items shifted to the Stereotypic Behavior factor. The CFA revealed a very poor fit with an RMSEA = .12 (Brown & Cudeck, 1993 in Brinkley et al., 2007) with the solution accounting for only 54% of variance. On the whole, Brinkley et al. (2007) asserted that the presence of a significant subgroup of individuals who were highly self-injurious likely accounted for some of the major differences between the ABC-C factor structure and the results generated in the Brinkley et al. (2007) study.

Overall, Brinkley et al. (2007) maintained that both their four-and five-factor solutions for ASD were similar to those found in previous factor analyses for non-ASD populations. However, divergent findings that arose from their analyses concerned the movement of most of the items on the original Irritability, Agitation, Crying factor to the Hyperactivity, Noncompliance factor and the emergence of a self-injurious behavior subset (which then encompassed the entire Irritability factor). The authors stated that this separate self-injurious behavior factor was also found in Marshburn and Aman (1992) and is worthy of further exploration (Marshburn & Aman, 1992 in Brinkley et al., 2007). Additionally, the authors

pointed out that because the ABC-Cs Irritability factor has been used to justify effects in psychopharmacology trials for ASD, it also merits more intensive analysis because it includes the self-injurious behavior items.

Mirwis (2011). In a published dissertation, Mirwis (2011) performed an EFA with an ASD population in order to assess the factor structure of the ABC-C for individuals with autism. The rationale for the dissertation stemmed from two key arguments. First, only one study, Brinkley et al. (2007), had assessed the ABC-C factor structure in an ASD sample at that point in time, so additional studies were clearly warranted. Second, Mirwis (2011) had methodological concerns with the basic approach that Brinkley et al. (2007) used in their analysis (i.e., PCA rather than an EFA for factor extraction). Mirwis (2011) argued that the PCA approach that Brinkley et al. (2007) used was conceptually inappropriate in that the PCA method derives factors from measured or observed variables only. Rather, Mirwis (2011) asserted that Brinkley et al. (2007) should have used the EFA method, which would have better uncovered the latent variable constructs in the ABC-C. Further, because Brinkley et al. (2007) also found a somewhat different factor structure from the ABC-C, even though the same number of factors, five, was retained in the final solution, Mirwis (2011) remarked that this potentially opened up more questions about how the ABC-C might function for individuals with ASD.

To perform the study, Mirwis (2011) sampled 236 individuals with ASDs (i.e., autistic disorder or PDD-NOS) ranging in age from three to 21 years old ($M = 8.5$, $SD = 4.5$) who attended a special education agency that served individuals with significant developmental disabilities. Inclusion criteria comprised the three to 21-year age range and an autistic disorder or PDD-NOS diagnosis. Students in agency classrooms presented with significant functional impairment as reflected in delays in cognition, adaptive behavior, and social and communication

skills. Mean IQ for the sample was 59. Special education staff members rated all individuals in the sample.

An EFA was performed using the principal axis factoring (PAF) extraction method on the Pearson correlation matrix, followed by three tests to determine the number of likely interpretable factors and whether the factors were correlated or not (i.e., the eigenvalue-greater-then-one rule, scree plot, and parallel analysis [Horn, 1965]), along with an oblique, promax (Hendrickson & White, 1964) rotation. Four different factor solutions were considered (five, six, seven, and eight). Following the EFA, concurrent validity analyses (convergent and divergent validity) were performed using the Pervasive Development Disorder Behavior Inventory (PDDBI; Cohen & Sudhalter, 2005) and the GARS-2 (Gilliam, 2006) as external criterion measures.

Mirwis (2011) ultimately decided on a seven-factor solution. Three of the factors clearly matched those found in prior ABC-C factor analyses. These were retained as Stereotyped Behaviors, Inappropriate Speech, and Hyperactivity, Noncompliance. However, four other factors resulted from the standard Irritability, Agitation, Crying and Lethargy factor and Social Withdrawal factor, each splitting into two factors. A separate Lethargy factor split off from the Social Withdrawal factor of the ABC-C, and a Self-Injurious Behavior factor split off from the Irritability, Agitation, Crying factor of the ABC-C. Interestingly, Mirwis (2011), like Brinkley et al. (2007), also found a cluster of three items that seemed to indicate an underlying self-injurious behavior factor. However, Brinkley et al. (2007) chose to retain the variables under the Irritability factor rather than split it off into a distinct factor like Mirwis (2011). Finally, Mirwis (2011) found moderate to strong evidence of convergent validity for several of the factors with similar conceptual scales on the PDDBI (Cohen & Sudhalter, 2005) and the GARS-2 (Gilliam,

2006) and evidence of divergent validity with those scales conceptually dissimilar. However, the PDDBI and GARS-2 did not allow for equivalent criterion constructs for some of the factors.

Overall, Mirwis (2011) concluded that the factor structure of the ABC-C may be different for individuals with ASD. Mirwis (2011) emphasized the need for more EFAs to better assess possible variability in the ABC-C factor structure for the ASD population. Mirwis (2011) also highlighted the continual emergence of the items that seem to underlie a Self-Injurious Behavior factor. These items, having been highlighted (at that point) in Brinkley et al. (2007) and also in Marshburn and Aman (1992)—although in that study with a non-ASD sample—point to a construct that may be particularly relevant for ASD populations and potentially non-ASD populations as well. Mirwis (2011) emphasized the need for further EFAs with large sample sizes to more thoroughly examine the existence of this factor.

Kaat et al. (2014). Kaat et al. (2014) conducted both an EFA and a CFA with an ASD population in order to assess the factor structure of the ABC-C for individuals with ASD. The impetus for performing the study centered around the fact that the ABC-C had become popular for individuals with ASD but still lacked a thorough psychometric analysis for the ASD population. Kaat et al. (2014) also took advantage of the large sample size they accessed for the study and cross-validated the results using split samples.

To perform the study, Kaat et al. (2014) sampled 1,893 individuals total between two and 18 years old (M = 6.5, SD = 3.6) culled from a network consisting of 17 children's hospitals in the US and Canada. Participants had all met criteria for autism or ASD based on the ADOS (Lord, Rutter, DiLavore, & Risi, 2000). Parents rated children on the ABC-C. The EFA included 1,130 participants while the CFA validation sample included 763 participants. Forty-seven percent of participants had an IQ of $\leq$ 70.

An EFA was performed using ordinary least squares estimation with an oblique quartimax rotation (Neuhaus & Wrigley, 1954) on the polychoric correlation matrix (Pearson, 1900) for the extraction method, followed by three methods to determine the number of factors that best fit the data (i.e., eigenvalue-greater-than-one rule, scree plot, and clinical meaningfulness). For the CFA, three previous factor models potentially relevant for ASD were analyzed—including Brinkley et al. (2007), as the only other model that was based on an ASD sample. The CFA was conducted using diagonally-weighted least squares estimation on the polychoric correlation matrix and sample-estimated asymptotic covariance matrix. Concurrent validity analyses were conducted using relevant scales from the ADOS (Lord et al., 2000), the Vineland Adaptive Behavior Scales-Second Edition (VABS-II; Sparrow, Cicchetti, & Balla, 2005), the Stanford Binet-Fifth Edition (SB-5; Roid, 2003), and the Child Behavior Checklist (CBCL; Achenbach & Rescorla, 2000, 2001).

Kaat et al. (2014) examined a four-, five-, and six-factor solution. Ultimately, they decided on a five-factor solution and found 90% of the ABC-C items loaded on the same factors as found for the original scale. The CFA analyzed the fit of the four-factor solution used by Brown et al. (2002), who sampled 601 children ages 6-22 (M = 13.2) with developmental disabilities in special education classes, rated by caregivers; the four- and five-factor solutions proposed by Brinkley et al. (2007); the six-factor solution by Sansone et al. (2012), who sampled 315 children and adults ages 3-25 (M =11.07) with Fragile X syndrome, rated by caregivers; and the original five-factor solution of the ABC by Aman et al. (1985a), which maintained the same factor structure and item loadings as the ABC-C (Aman & Singh, 1994). The four-factor model by Brown et al. (2002) resulted in a weak fit (RMSEA = .12), but the other four-, five-, and six-factor models all yielded a somewhat better and similar degree of fit, with RMSEAs ranging

from .081 to .086. Notably, Kaat et al. (2014) remarked that they decided upon retaining the five-factor solution of the ABC after the CFA, despite an RMSEA = .086, because of the "historical basis and widespread use of the original factor structure and results of other factor analytic studies" on the ABC-C citing a "historical and pragmatic perspective" (p. 1107). Further, Kaat et al. (2014) found that participant age, sex, and IQ were mostly "unrelated" to the ABC-C scale scores (p. 1107). In general, appropriate convergent and divergent validity was found between the newly factor analyzed ABC-C scores and the different external measures used for comparison—though the external criterion measures were not able to exactly or closely represent some of constructs required by the ABC-C factors.

Overall Kaat et al. (2014) concluded that the original, five-factor structure of the ABC-C was likely strong for the ASD population. The authors did acknowledge the "less-than-optimal model fit" of the model with the RMSEA above .08; a Standard Root Mean Square Residual (SRMR) at .10, rather than the more ideal < .05 (Browne & Cudeck, 1992 in Kaat et al., 2014, p. 1112); and the Satorra-Bentler Chi-square ($SB\ \chi^2$) statistic that was statistically significant, meaning that there is a statistically significant difference between the actual and proposed models. Kaat et al. (2014) remarked that a few "item pairs or triplets evidence a high degree of residual covariance" could allow for a more complicated factor structure but that they chose to maintain the current model because it was more "practical" and "parsimonious" (p. 1112). This residual (unmodeled) covariance could also provide evidence of more factors or, as the authors maintain, a more complicated factor solution.

Three other results are important to note. First, Kaat et al. (2014) highlighted the fact that two items that previously loaded on the Hyperactivity/Noncompliance factor loaded on the Irritability, Agitation, and Crying subscale—although high cross-loadings were found as well.

Kaat et al. (2014) dismissed this as "due to sample artifacts" and not evidence of a problem with the model (p. 1112). Second, Kaat et al. (2014) remarked that a three-item Self-injurious behavior (SIB) factor emerged in the six-factor solution. The authors stated: "when present, the SIB is often highly clinically significant" although they asserted that it is not core to ASD diagnostic symptomology (Kaat et al., 2014, 1112). They argued that including a sixth factor did not greatly improve the model fit. Finally, the authors addressed the fact that the Lethargy, Social Withdrawal factor remained intact in their model though it was split into two factors in Sansone et al. (2012), one of the models used in the CFA. Kaat et al. (2014) highlighted the fact that the Sansone et al. (2012) model was based on a sample of individuals with Fragile-X syndrome and overall did not result in a model that was greatly superior to their five-factor solution. However, Kaat et al. (2014) did raise the question as to whether there is a justification for "an alternative scoring method" for individuals with particular syndromes, although ultimately Aman and Singh (2017), the original test authors, emphatically advised against it (Aman & Singh, 2017, p. 1113).

Summary of the EFAs of the ABC-C for the ASD population. Both Aman and Singh (2017) and Mirwis (2011) reviewed the various factor analyses of the ABC and ABC-C. However, both developed distinctly different conclusions about the robustness of their factor structures. According to Aman and Singh (2017), the factor structure of the ABC-C has been replicated multiple times, regardless of changes in age range, environments, types of raters, and even language translations. The authors also claimed that there was a high level consistency among items loading on the same factors across the various factor analytic studies of the ABC and the ABC-C (i.e., average overlap across 14 studies was 85% of all 58 items; Aman & Singh, 2017). Further, they stated that coefficient alphas and Harman's coefficient of congruence were

consistently strong across these 14 studies, despite the fact that the CFAs performed on the ABC and ABC-C were not found to result in strong model fits (Aman & Singh, 2017). Overall, Aman and Singh (2017) concluded that taken together, the various factor analytic studies of the ABC and ABC-C consistently supported the five-factor structure.

On the other hand, Mirwis (2011) argued that there have been various methodological flaws across the different factor analytic studies that make it inappropriate to reach strong conclusions. In particular, Mirwis (2011) contended that many of the factor analytic studies failed to examine solutions greater than or less than five factors. In those studies that did so, the authors often chose different solutions (Mirwis, 2011).

Overall, there is disagreement between the test authors (Aman & Singh, 2017) and Mirwis (2011) regarding the robustness of the factor structure for the ABC-C. Thus, there is a clear need for analyses using new samples and employing rigorous methods to examine the factor structure of the ABC-C in persons with ASD. This dissertation will take a step toward meeting that need by examining the factor structure of the ABC-C with samples of individuals with ASD as rated by special education staff members

Variables of Sample Characteristics

Given the variety of participants measured with the ABC-C—and in particular the subjects to be focused on in this study—it is necessary to address the influence that certain variables may have on outcomes for individuals with ASD. Mayes and Calhoun (2011) looked into the influence of age, SES, gender, race, and IQ on ASD symptomology. The authors found no significant effects of race, SES, and gender but found that IQ and age did affect the severity of symptoms. In the three EFAs performed of the ABC-C with individuals with ASD (Brinkley

et al., 2007; Kaat et al., 2014; Mirwis, 2011), only Kaat et al. (2014) addressed the influence of demographic variables on their results.

Kaat et al. (2014) looked at the correlations between ABC-C subscale scores and external variables including sex, IQ, and age, and concluded that the effects were relatively minor. They found no major effects with regard to sex, similar to Mayes and Calhoun (2011). They did find that an increase in age was associated with decreases in Irritability (r = -.13) and Hyperactivity (r = -.16). Lower IQ scores were associated with increases in Stereotypic Behavior (r = -.19), Social/Withdrawal (-.12), and Inappropriate speech (-.09). Results also showed that adaptive behavior, particularly with regard to communication, was more highly correlated than IQ with regard to ABC-C scores. Kaat et al. (2014) also found minor effects for the influence of age and IQ when their reference group was divided into groups < 6 years old, 6 to < 12 years old, > 12 years old, and split between individuals with IQ scores of < 70 and > 70, though the authors highlight the fact that all the effects were small. Effects were found for age on the Irritability, Social Withdrawal, and Hyperactivity/Noncompliance subscales with ω^2 ranging from .001 to .003. IQ was found to affect Social Withdrawal (ω^2 = .007) and Stereotypic Behavior (ω^2 = .001), and a significant interaction was found between IQ and age for Inappropriate Speech (ω^2 = .005). Overall, as shown in Kaat et al. (2014), there are some variables that have minor effects on the mean scores for particular factors. Mean score differences (e.g., for age and sex) are addressed in reference group scoring data for the ABC-C in the manual (Aman & Singh, 2017).

Kaat et al. (2014) also explored whether particular variables could have substantial effects on the factor structure of the ABC-C. Kaat et al. (2014) divided their calibration sample for their CFA by age at 6 years (older and younger), IQ at 70 (above and below) and by ADOS comparison score (above and below 7) to see whether or not these variables had significantly

influenced the model fit. A marginal fit was found across all samples with RMSEAs ranging from .081 to .092 and Standard Root Mean Square Residuals (SRMR) ranging from .10 to .11, with little difference found between the different groups. As such, these demographic variables did not seem to have a great effect on the model fit of the five-factor structure and thus, did not seem to have great influence on the overall five-factor solution.

The effects of certain demographic variables on the ABC-C subscale scores found in Kaat et al. (2014) indicated small effect sizes that could be explored in future studies once the factor structure of the ABC-C is clearer for the ASD population. However, although these variables are included in the sample description, the relative influence of certain demographic variables on outcomes is not a focus of this study. Thus, no specific hypotheses will be included on the topic. The purpose of this study will be more limited to examining the factor structure of the ABC-C with an ASD sample.

Purpose of the Current Study

The purpose of the current study is to examine the psychometric properties of the ABC-C with an ASD sample as rated by special education staff. There are four specific gaps in the research literature that this study will help to address. First, despite the instrument's immense popularity within the ASD research community, there has not been sufficient research performed on the factor structure of the ABC-C with ASD samples. As such, there is still ambiguity and a lack of evidence regarding the most appropriate factor structure for the ABC-C when used with the ASD population. Of note, a strong argument could be made regarding the lack of evidence for an appropriate factor structure for the ID population as well, the scale's initially intended population, though this study will not explore that line of argument. Second, the factor analyses that have been performed with the ABC-C have not been as rigorous as they could be according

to current best practices (e.g., Norris & Lecavalier, 2010b), most notably that alternative factor structures were often not fully and appropriately explored in EFA nor tested in CFA. Third, as mentioned previously, only one study, Mirwis (2011), used special education staff to rate participants with ASD. As indicated, his solution currently exists as an outlier compared to the other EFAs. This could indicate that raters from this environment are bringing a unique perspective to their ratings compared to caregivers, and could, in turn, affect outcomes. Thus, it is important to explore the robustness of the findings by Mirwis (2011) with a similar sample of subjects and raters as well as try and improve upon the rigor of his analysis. Fourth, no study has performed a CFA on the ABC-C directly comparing all the models generated with ASD samples (Brinkley et al., 2007 Kaat et al., 2014; Mirwis, 2011). This study provides an opportunity to do so and also will include a model generated through the EFA in this study as well.

Of note, there is an argument to make for excluding an EFA analysis altogether and performing only a CFA to test the different solutions that have been found amongst the three available studies for the ASD population. However, given the lack of methodological rigor in Brinkley et al. (2007), and the suspect factor solution selection criteria used by Kaat et al. (2014), there is a strong possibility that a different factor solution could exist that has not been appropriately explored. Constraining the CFA to the existing models only without first performing a more thorough EFA prior could potentially result in having to accept a less rigorous model. Thus, it is likely more advantageous to perform due diligence with the EFA first and complement it with a more effective CFA.

Further justification for the study is also noted in the aforementioned SEPT (2014) standards with regard to *validity*, *fairness,* and *test design and development* (see Tables 1, 2, and 3 for details). With regard to *validity*, Standards 1.1, and 1.3 highlight the fact that a test is not

valid for “all purposes or in all situations” and that when a new situation arises validation is required (SEPT, 2014, p.23). It is argued herein that adequate validity has not been satisfactorily established for the ASD population with the ABC-C and further validation is necessary. In addition, according to Standard 1.4, with regard to the use of the ABC-C in a different way that has not been thoroughly validated, further exploration is also necessary to help determine whether the choice of using raters from a special education environment might result in a different factor structure, as was found in Mirwis (2011).

With regard to the SEPT standards for *fairness*, Standard 3.3 highlights the importance for relevant subgroups to have been included when developing the ABC-C. The ABC-C was initially intended for the ID population, not for the ASD-population. The ABC-C has now been used in very consequential studies by multiple ASD researchers despite the fact that this population was not assessed during the initial development. Aman and Singh (2017) seem to imply in the ABC-C2 manual that because the ASD population falls under the ID/developmental disabilities population, it is unnecessary to explore whether there is potentially a different factor structure (p. 54). Recent research (e.g., Kurzius-Spencer et al., 2018) has shown that there are distinctive behavioral differences between the ID and ASD populations, despite an overlap of symptomology and common comorbidity. Therefore, it is argued that it is most sensible to further assess the factor structure of the ABC-C for the ASD population.

Finally, with regard to the SEPT standards for *test design and development*, Standards 4.0, 4.1, and 4.6 maintain a similar spirit to the standards provided for *validity*, though with a more specific focus on test development processes. Once again, the ABC-C was not initially developed for the ASD population and it is the contention herein that adequate evidence for the structure of the ABC-C with an ASD population has not been shown, thereby requiring further

analysis. Standard 4.24 goes one step further however and highlights the fact that when new data arises, test specifications may need to be amended or revised. It was argued previously that the factor analyses by Brinkley et al. (2007), Mirwis (2011), and Kaat et al. (2014) revealed data that called into question both the current factor structure of the ABC-C for the ASD population and the conclusions arrived at by the ABC-C test authors (Aman & Singh, 2017). Thus, following the essence of this standard, it is necessary to further explore the ABC-C factor structure with the ASD population to determine whether the scale requires revision for this population.

Specifically, the following five questions will be addressed. (Note that research questions, hypotheses, and associated justifications are covered in more detail within the method section. Research questions one through four will be covered within the method subsection for study one and research question five will be covered within the method subsection for study two.)

Research Questions

Questions one through four, described below, will be investigated via exploratory factor analytic techniques. Question five will be investigated via confirmatory factor analytic techniques.

Research question 1. Based upon ratings of a sample of individuals with ASD by special education staff, how many possible or likely interpretable ABC-C factors are available for retention consideration?

Research question 2. How many factors should be retained in order to derive the most interpretable factor solution?

Research question 3. Does the most interpretable factor structure yield substantive correlations amongst the factors?

Research question 4. If a five-factor solution is interpretable (and even if it is not the retained solution), to what extent does the solution correspond to the five factors hypothesized by the test authors?

Research question 5. How does the factor solution generated in a sample of individuals with ASD rated by special education staff members for the ABC-C compare in terms of absolute and relative fit to previous ABC-C factor models found in ASD samples or proposed for use with individuals with ASD?

CHAPTER 3: METHOD

Two studies were performed in this dissertation. The first study consisted of an exploratory factor analysis (EFA), encompassing research questions one through four. The second study was a confirmatory factor analysis (CFA), which was dependent upon the outcome of study one and addresses research question five. The research design and procedures used to collect extant data will be discussed. This will be followed by the hypotheses and method for study one, and the hypothesis and method for study two.

Research Design

The focus of study one and study two is on instrument validation, in terms of internal structure and model fit, with an ASD sample and special education staff raters. From a design perspective (e.g., Kazdin, 2017), such studies are observational, correlational, and cross-sectional in nature, and involve multivariate statistical techniques intended to examine latent structures and their meaning. Factor analytic techniques were used to reduce derived inter-item correlations to the most useful and interpretable number of potential explanatory variables. Factor-based scales were constructed and the model was tested against existing competing models to determine the best structural fit.

Extant Data Collection

Data for study one were extracted from a large existing data set of special education staff ratings of individuals with ASD from a center-based, special education agency in western New York State that serves students with developmental disabilities. Data for study two comes from the same center-based special education agency in western New York State. Though many of the cases used in study two overlap with the larger sample to be used for the EFA, some cases come from program evaluation periods other than those used for the EFA.

Of note, extant data collection methods for these two studies were similar to those used in the ABC-C EFA study by Mirwis (2011), as well as the EFA of the SRS-2 (Constantino & Gruber, 2012) by Nelson (2015), and the EFA of the GARS-2 (Gilliam, 2006) by Dua (2014). This includes similar recruitment procedures and subject participation from a comparable population as well as analogous procedures for data entry and analysis.

Raters. Data in the extant datasets consist of participant ratings made by special education staff members, which comprised individuals working in the special education classroom environment who have intimate knowledge of students in this context. Special education staff members include special education teachers, teaching assistants, speech pathologists, physical therapists, occupational therapists, behavior technicians, individual student aides, whole classroom aides, and trained volunteer assistants associated with the agency described above. A multitude of raters were chosen by the agency to ensure that there would be a one-to-one correspondence with regard to rater and student. Ratings occurred on an annual basis as part of the agency's regular program evaluation process from 2005 through 2018. Staff psychologists assigned raters to particular students. Each rater was assigned a single student to rate, which maintained independence across ratings. Rater familiarity with each student ranged in time from six weeks to twenty-eight months of interaction. Despite familiarity with the students, raters were not typically aware of formal, individual student diagnoses, although the majority of raters were aware of the nature of ASD symptomology as a result of their experience working in the special education environment.

Procedures. Procedures for obtaining rating scale data in the extant data set were developed by the special education agency for their annual program evaluation process. Each case was assigned a packet of rating measures to be completed by the designated rater. Each

packet contained between three and five rating instruments. Measures were counter-balanced at random within each packet and staff members were instructed to complete them in the order given. All possible instrument orders were represented.

Each completed protocol was checked by a program evaluation staff member in order to detect missing item responses or items with additional mistaken responses. Problematic items were resolved by contacting the rater. Once measure forms were determined to be complete, two program evaluation staff members independently scored each one. Scoring discrepancies were resolved by a third program evaluation staff member.

Each case in the dataset was assigned a unique ID code by the director of program evaluation at the agency. Only the director of program evaluation at the agency had the list of identifying information linked to each code. The investigator for these studies did not have access to any individual identifying information beyond the case ID code.

Inclusion/exclusion criteria. Participant suitability for study inclusion was determined by a three-stage screening process including (a) chronological age parameters between three and 21 years old; (b) a clinical diagnosis of autistic disorder or PDD-NOS based on DSM-IV-TR (APA, 2000) criteria or an ASD diagnosis based on DSM-5 (APA, 2013) criteria as determined by a licensed psychologist or licensed medical professional, or an ASD special education eligibility designation as determined by the participants' school-based special education committee; and (c) current participation in special education classrooms appropriate for students with substantial functional impairment (e.g., individuals with significant delays in cognitive, social, and communication domains with Intelligence Quotient [IQ] typically in the cognitive impairment/intellectual disability range). Cognitive data for participants were derived from a variety of measures, including: the Bayley Scales of Infant Development, (Bayley, 1969), Bayley

Scales of Infant Development, Second Edition (Bayley, 1993), Bayley Scales of Infant Development, Third Edition (Bayley, 2006), Stanford-Binet Intelligence Test, Fourth Edition (Thorndike, Hagen, & Sattler, 1986), Stanford-Binet Intelligence Test, Fifth Edition (Roid, 2003), the Comprehensive Test of Nonverbal Intelligence (Hammill, Pearson, & Wiederholt, 1996), the Cognitive Assessment System, Second Edition (Naglieri, Das, & Goldstein, 2014), the Differential Ability Scales (Elliott, 1990), the Differential Ability Scales, Second Edition (Elliott, 2007), the Kaufman Assessment Battery for Children (Kaufman & Kaufman, 1983), the Kaufman Brief Intelligence Test (Kaufman & Kaufman, 1990), the Learning Accomplishment Profile-Diagnostic Standardized Assessment (Nehring, Nehring, Bruni, & Randolph, 1992), the McCarthy Scales of Children's Abilities (McCarthy, 1972), the Universal Nonverbal Intelligence Test (Bracken & McCallum, 1998), the Wechsler Abbreviated Scale of Intelligence (Wechsler, 1999), the Wechsler Abbreviated Scale of Intelligence, Second Edition (Wechsler, 2011), the Wechsler Adult Intelligence Scale, Third Edition (Wechsler, 1997), the Wechsler Intelligence Scale for Children, Revised (Wechsler, 1974), the Wechsler Intelligence Scale for Children, Third Edition (Wechsler, 1991), the Wechsler Preschool and Primary Scale of Intelligence, Revised (Wechsler, 1989), the Wechsler Preschool and Primary Scale of Intelligence, Third Edition (Wechsler, 2002), and the Wechsler Preschool and Primary Scale of Intelligence, Fourth Edition (Wechsler, 2012). No single measure was used consistently for all participants due to variable ages, behavioral challenges, and communication skills of the participants. All cognitive scores were set to a deviation quotient (DQ) metric, with a normative mean of 100, and a standard deviation of 15, in order to allow for some limited comparability of participants' cognitive scores. Only the most recent cognitive test information available for each participant was used.

Study One: EFA

Research questions, rationales, and hypotheses. Research questions one through four were addressed through the EFA. Table 11 contains a summary of the four research questions for study one and the EFA statistics that were used to determine their outcomes.

Research question 1. Based upon ratings of a sample of individuals with ASD by special education staff, how many possible or likely interpretable ABC-C factors are available for retention consideration?

Research rationale and hypothesis 1. Among the three prior factor analyses that were performed on the ABC-C with an ASD population (Brinkley et al., 2007; Kaat et al., 2014; Mirwis, 2011) between four and eight interpretable factors were found to be available for retention. Brinkley et al. (2007) considered a four-factor and a five-factor solution, which they stated were based closely upon previous analyses performed with the ABC and ABC-C. Results from the Guttman-Kaiser criterion and scree test—the analyses they used to help determine the number of factors to retain—were not provided and no explanation was offered as to why they did not examination other possible factor solutions. Kaat et al. (2014) considered a four-, five-, and six-factor solution, although they found 11 eigenvalues > 1. The authors also reported that a scree plot analysis supported a five-factor solution—which is what they ultimately retained. Mirwis (2011) considered between five and eight factors in his analysis and retained a seven-factor solution. Therefore, based upon previous factor analyses with the ABC-C with an ASD population, it is hypothesized that there will be between four and seven interpretable factors available for retention. Possible factor solutions for further examination will be determined using Principal Axis Factoring (PAF) along with the Guttman-Kaiser criterion (Guttman, 1954; Kaiser, 1960), the scree test (Cattell, 1966), parallel analysis (Horn, 1965) and the minimum

average partial test (MAP; Velicer, 1976). Depending upon the level of agreement amongst the various criteria, a range of factor solutions will be explored (e.g., solutions consisting of the consensus number of factors plus or minus two factors will denote the range to be examined for interpretability).

Research question 2. How many factors should be retained in order to derive the most interpretable factor solution?

Research rationale and hypotheses 2a, 2b, and 2c. Previous factor analyses with the ABC-C performed with an ASD population (i.e., Brinkley et al., 2007; Kaat et al., 2014; Mirwis 2011) have resulted in four-, five-, and seven-factor solutions. Brinkley et al. (2007) found both a four-factor solution (Hyperactivity, Lethargy, Stereotypy, Irritability) and a five-factor solution (Hyperactivity, Lethargy, Stereotypy, Irritability, Inappropriate Speech). Mirwis (2011) chose a seven-factor solution (Irritability, Hyperactivity, Withdrawal, Lethargy, Stereotyped Behaviors, Inappropriate Speech, and Self-Injurious Behavior), which included splitting the Lethargy, Social Withdrawal factor on the ABC-C into two separate factors and included a separate Self-Injurious Behavior factor consisting of three items usually assigned to the Irritability factor. Kaat et al. (2014) selected a five-factor solution (Irritability, Lethargy, Social Withdrawal, Stereotypic Behavior, Hyperactivity/Noncompliance, and Inappropriate Speech) consistent with the standard five subscales posited by the authors of the ABC-C. Across the three studies, factors consistent with Hyperactivity, Lethargy, Stereotypy, and Irritability constructs have all been retained. Each of the studies also discovered evidence of a self-injurious behavior factor, with Mirwis (2011) choosing to retain it, Brinkley et al. (2007) simply keeping the *Irritability* factor name—though only self-injurious behavior items loaded on the factor in both the four-and five-factor solutions—and Kaat et al. (2014) deciding to discard it. Only the factor analysis by

Mirwis (2011) used ABC-C ratings completed by special education staff for an ASD population. Therefore, based upon previous factor analyses, three hypotheses will be made: a) at least four factors will likely be retained, b) an Inappropriate Speech factor will appear, and c) a Self-Injurious Behavior factor will also appear. All three hypotheses will be determined by examining the pattern and structure matrices (resulting from oblique direct oblimin rotation [Jennrich & Sampson, 1966]) for interpretability of factors across the range of possible factor solutions (i.e., possible factor solutions suggested by the combination of the Guttman-Kaiser criterion, the scree test, parallel analysis, and the MAP test).

Research question 3. Does the most interpretable factor structure yield substantive correlations amongst the factors?

Research rationale and hypothesis 3. Analyzing correlations amongst factors helps to elucidate the nature of the underlying constructs within the data (Fabrigar et al., 1999). The degree to which factors are correlated is often indicative of the strength of the conceptual relations among the factors. Depending upon the nature of the scale, certain constructs should be more correlated (e.g., Hyperactivity and Irritability) or less correlated (Inappropriate Speech and Lethargy, Social Withdrawal). This can provide further evidence for the validity of factor-naming choices. If substantive enough, such correlations could also reveal the presence of higher-order factors, which could represent the statistical and conceptual basis for one or more composite scores. Aman and Singh (2017) argued that an overall composite score for the ABC-C would be "a mish-mash of problem behaviors that have no clinical or empirical meaning," (p. 56). Brinkley et al. (2007) did not report inter-factor correlations. Kaat et al. (2014) reported inter-factor correlations ranging from .09 (Inappropriate Speech and Stereotypic Behavior) to .50 (Hyperactivity/Noncompliance and Irritability) but did not fully explore their potential

implications. Mirwis (2011) reported inter-factor correlations ranging from .05 (Inappropriate Speech and Self-Injurious Behavior) to .55 (Irritability and Hyperactivity), but also did not comment on any potential implications. Therefore, based upon the EFAs by both Mirwis (2011) and Kaat et al. (2014), it is hypothesized that there will be substantive correlations (i.e., > .30; Beavers et al., 2013) among at least some factors. This will be determined by analyzing the relations in the inter-factor correlation matrix of the chosen factor solution after the oblique rotation.

Research question 4. If a five-factor solution is interpretable (and even if it is not the retained solution), to what extent does the solution correspond to the five-factors hypothesized by the test authors?

Research rationale and hypothesis 4. Aman and Singh (2017), the ABC-C test authors, insist that the five-factor solution of the ABC-C has now been continuously supported by prior factor analyses. The authors also argued that the development of syndrome-specific scales (such as for ASD) is counterproductive because it would open up the possibility of having to develop various scales for the different syndrome populations. It is beyond the scope of this dissertation to debate the extent to which arguments that Aman and Singh (2017) make regarding this issue have merit, but it is worthwhile to determine whether or not their preferred factor solution is actually most appropriate for the ASD population. Curiously, the CFA that Kaat et al. (2014) performed showed little difference between the strength of a five-and six-factor model, yet they continued to maintain the five-factor solution, based on historical precedent. Mirwis (2011) found a five-factor solution that was similar to the ABC-C factor structure (Irritability, Lethargy, Stereotypic Behavior, Hyperactivity, and Inappropriate Speech), though reasoned that a seven-factor solution was more conceptually meaningful and the most appropriate. Thus, in order to

maintain an open and generally exploratory approach to the analysis, and limit any preconceived outcomes, it is necessary to rigorously assess the strength of all derived solutions—keeping in mind that the retained solution may differ from the long maintained five-factor solution. Furthermore, it is important to analyze any derived five-factor solution from the present study data to examine the extent to which it corresponds to the test authors' expectations. This solution has become a traditional, interpretative framework for the instrument despite the fact that the majority of studies of the ABC and ABC-C have not broadly explored nor examined a large range of potential factor solutions. Therefore, based on previous factor analyses, it is hypothesized that the five-factor solution, from among the possible EFA solutions, will closely match the test-authors' proposed five-factor solution. (Though assessed through an EFA procedure open to any five factors appearing, this hypothesis is conceptually confirmatory in its expectation that the five-factor solution emerging from the EFA will closely resemble the traditional ABC-C five factors. However, the traditional five-factor model is not being pre-specified and assessed for fit as it would through a CFA conducted via structural equation modeling.) This hypothesis will be examined in three ways. First, by qualitatively comparing the factor construct names of the test authors' five-factor solution and this study's derived five-factor solution. Second, qualitatively comparing the highest loading items that are instrumental in defining each factor on the test author's solution and this study's derived solution. Third, by calculating a percentage of overlapping items between the factors from the derived five-factor solution and the ABC-C authors' version. (This hypothesis should in no way be interpreted as assuming that the five-factor model will likely be retained as the most interpretable and meaningful EFA solution. It is possible that other interpretable factor solutions may be more conceptually meaningful and account for more variation.)

Table 11. *Summary of Study One Research Questions*

Research Question Number	Research Question	Hypothesis	Analysis	Method(s)
1	How many possible or likely interpretable factors?	Between four and seven factors	Guttman-Kaiser criterion, scree test, MAP test, parallel analysis	EFA with principal axis factoring
2	How many factors should be retained?	2a) At least four factors will be retained 2b) There will be an inappropriate speech factor 2c) There will be a self-injurious behavior factor	Examine the interpretability of the pattern and structure matrices for the range of solutions suggested by the factor retention methods above (i.e., Guttman-Kaiser, scree, MAP, parallel analysis)	EFA with oblique rotation, pattern and structure matrices
3	Are there substantive correlations amongst the factors	Yes, among some of the factors	Analyze the relations in the inter-factor correlation matrix of the chosen factor solution	EFA with oblique rotation
4	How well does the obtained five-factor solution correspond to the test authors' five-factor model?	It will closely match the test authors' solution	Qualitatively compare factor names and highest loading items between the ABC-C authors' five-factor solution and the derived five-factor solution in this study, and calculate a percentage overlap in items between the obtained solution and the ABC-C authors' model for each factor	Qualitative comparison, percentage item overlap calculation per factor

Study one sample demographics. The sample for study one consisted of 300 ASD cases. Sample participants included 80.0% males (*n* = 240) and 20.0% females (*n* = 60), ranging in age from 3.17 to 21.05 years (*M* = 9.17, *SD* = 4.38; See Table 12). Note that the obtained sample male-to-female ratio of 4:1 is similar to the best available population-level estimate of the ratio in ASD of 4.5:1 (see Baio et al., 2018). Ethnic identification included 76.3% white/non-Hispanic (*n* = 229), 11.0% black/African-American (*n* = 33), 5.3% Hispanic (*n* = 16), 2.0% Asian American (*n* = 6), 2.3 % other (*n* = 7), 3.0% unknown (*n* = 9). Socioeconomic data were not consistently available in individual participants' records; however, agency-level data indicated that 29%-36% of students qualified for free or reduced lunch (FRL)—depending on the program evaluation year. FRL is often used as a proxy for socioeconomic status despite the fact that there are various acknowledged issues with the correlation (e.g., Harwell & LeBeau, 2010; Nicholson, Slater, Chriqui, & Chaloupka, 2014; Snyder & Musu-Gillette, 2015).

Cognitive deviation quotient scores (DQ) ranged from 12 to 112 (*M* = 56.49, *SD* = 18.25), with 74.6% of the sample with DQ scores ≤ 70 (i.e., at least two standard deviations below the mean), and 93.2% ≤ 85 (i.e., at least one standard deviation below the mean). Of note, previous researchers have included individuals with higher IQ scores in factor analyses of the ABC-C with an ASD sample (e.g., Kaat et al., 2014, had 53% of their sample [n = 1893] with IQ's ≥ 70). Nonetheless, all individuals included in the sample in this study had substantial functional impairments in the cognitive, social, or communication domains (or some combination of the three) severe enough to warrant participation in special education classrooms.

Table 12. *Demographic Characteristics of Study One Sample*

	Sample *N* (%)	Mean (*SD*)	Range
Participant Gender			
Male	240 (80.0)		
Female	60 (20.0)		
Participant Race/Ethnicity			

Table 12 (cont'd)

White/Non-Hispanic	229 (76.3)		
Black/African-American	33 (11.0)		
Hispanic, No Race Specified	16 (5.3)		
Asian American	6 (2.0)		
Other	7 (2.3)		
Unknown	9 (3.0)		
Participant Age	300 (100)	9.17 (4.38)	3.17-21.05
Participant Deviation Quotient Score	295 (98.3)	56.49 (18.25)	12-112
Unknown	5 (1.7)		

Note: All cognitive scores were set to a deviation quotient (DQ) metric (i.e., normative mean of 100, standard deviation of 15) in order to allow for some limited comparability of participants' cognitive scores.

Measure for study one. The Aberrant Behavior Checklist-Community, Second Edition (ABC-C2; Aman & Singh, 2017) represents the third iteration of the original ABC (Aman & Singh, 1986), and the second edition of the original ABC-C manual. The ABC-C2 manual maintains that the current, third iteration of the ABC-C has the same number of items, item wording, and item scales as the second iteration of the ABC-C, although with minor updates on the subscale names (Aman & Singh, 2017). Despite the new manual and updated subscale names, the scale is still referred to as the ABC-C.

The ABC-C is designed to be administered by "anyone who has a good knowledge of the individual's behavior" (i.e., any stakeholder, be they a relative, teacher, care staff, or other professional) and who is familiar with the individual under various circumstances (Aman & Singh, 2017, p. 42). No specific time frame for knowing the individual is provided. Each of the 58 items on the ABC-C is rated on a four-point problem severity scale ranging from zero to three. Scale response anchors are *not at all a problem* = 0, *the behavior is a problem but slight in degree* = 1, *the problem is moderately serious* = 2, and *the problem is severe in degree* = 3. The most recent iteration of the ABC-C includes five subscales based on the Principle Components Analysis (PCA) from the original ABC: Irritability (containing 15 items), Social Withdrawal (containing 16 items), Stereotypic Behavior (containing 7 items),

Hyperactivity/Noncompliance (16 items), and Inappropriate Speech (4 items; Aman & Singh, 2017). According to the test authors in the ABC-C2 manual, these subscale names have been updated from the previous iterations of the ABC and ABC-C, though no explanation is provided to clarify what prompted the name changes (Aman & Singh, 2017).

ABC-C reliability. Internal consistency reliability is reported in the manual for the first iteration of the ABC (Aman & Singh, 1986), though not in the supplemental manual for the ABC-C (Aman & Singh, 1994) or the ABC-C2 manual (Aman & Singh, 2017). The internal consistency statistics (i.e., Cronbach's alpha; Cronbach, 1951) as reported for the ABC, calculated for a sample from institutional settings with intellectual disabilities, were as follows: Irritability, Agitation, Crying ($\alpha = .92$); Lethargy, Social Withdrawal ($\alpha = .91$); Stereotypic Behavior ($\alpha = .90$); Hyperactivity/Noncompliance ($\alpha = .95$); and Inappropriate Speech ($\alpha = .86$; Aman & Singh, 1986; Aman et al., 1985a). Additionally, in the Kaat et al. (2014) study of the ABC-C with a large sample of individuals with ASD, internal consistency reliability statistics were calculated within the CFA framework for both the calibration and validation samples: Irritability ($\alpha = .90, .92$); Lethargy/Social Withdrawal ($\alpha = .88, .89$); Stereotypic Behavior ($\alpha = .87, .85$); Hyperactivity/Noncompliance ($\alpha = .94, .93$); and Inappropriate Speech ($\alpha = .77, .77$).

Reliability for the ABC-C is reported in the ABC-C2 manual (Aman & Singh, 2017) in only two specific ways: (a) interrater reliability and (b) test-retest reliability. Summarizing across reported Pearson's *r*, Spearman's *rho*, and Intraclass correlation coefficients from the various ABC-C studies indicated the following: interrater coefficients for the Irritability subscale ranged from .53 to .90 (*Mdn* = .64), for the Social Withdrawal subscale they ranged from .12 to .88 (*Mdn* = .69), for the Stereotypic Behavior subscale they ranged from .42 to .76 (*Mdn* = .71), for the Hyperactivity/Noncompliance subscale they ranged from .45 to .81 (*Mdn* = .68), and for

the Inappropriate Speech subscale they ranged from .58 to .89 (*Mdn* = .74; Aman & Singh, 2017, p. 36-37).

Aman and Singh (2017) provided multiple reasons why the reliability coefficients for each scale vary widely. This included ratings performed by raters who held different roles or were in different settings (e.g., teacher vs. parent), and even an example where one of the studies assessed behavior over an 8-hour time frame—which is too brief a time interval to assess behavior for the way the scale was intended to be used. Miller, Fee, and Netterville (2004) looked at interrater reliability for teachers and teaching assistants (n = 22) using the ABC-C. They found that reliability coefficients ranged from .72 on the Stereotypic Behavior subscale to .80 on the Hyperactivity/Noncompliance subscale, though they did not provide coefficients for the other three subscales.

With regard to test-retest reliability, Aman and Singh (2017) highlighted four studies with the ABC-C with differences in test-retest intervals ranging between two weeks and four weeks (Miller et al., 2004; Ono, 1996; Schroeder et al., 1997; Siegfrid, 2000, as cited in Aman & Singh, 2017). Summarizing across reported Pearson's *r*, Spearman's *rho*, and Intraclass correlation coefficients from the studies based on the ABC-C indicated the following: Irritability subscale test-retest coefficients ranged from .59 to .98, Social Withdrawal subscale ranged from .76 to .96, Stereotypic Behavior subscale ranged from .75 to 1.00, Hyperactivity/Noncompliance subscale ranged from .75 to .94, and Inappropriate Speech subscale ranged from .52 to .98 (Aman & Singh, 2017).

Given that this study involves ratings by teaching staff members, a study with a similar group of raters using the ABC-C, such as in Miller et al. (2004), is useful for comparison. Across n = 47 cases rated by teachers with a two week test-retest interval, Miller et al. (2004)

found correlation coefficients of .68 for Inappropriate Speech, .77 for Stereotypic Behavior, .84 for Lethargy/Social Withdrawal, and .85 for Hyperactivity/Noncompliance and Irritability. Miller et al. (2004) also reported that across n = 22 cases rated by teaching assistants with a two-week test-retest interval, correlation coefficients were .74 for Inappropriate Speech, .81 for Hyperactivity/Noncompliance, .84 for Lethargy/Social Withdrawal, .89 for Irritability, and 1.00 for Stereotypic Behavior. Referencing guidelines for conceptualizing reliability provided by Cicchetti and Sparrow, Aman and Singh (2017) asserted that there was strong evidence that test-retest reliability was highly acceptable for the ABC-C subscales in most cases (Cicchetti & Sparrow, 1981, as cited in Aman & Singh, 2017).

ABC-C validity. Evidence concerned with the internal structure, concurrent validity, discriminant validity, and criterion-related relationships with behavioral observations of the ABC-C were reported in the ABC-C2 test manual (Aman & Singh, 2017). With regard to internal structure, a variety of factor analytic studies with individuals with intellectual disabilities have suggested a five-factor structure for the ABC-C (e.g., Aman et al., 1985a; Aman et al., 1995). However, the generalizability of this factor structure to other groups, such as individuals with ASD, is in question (e.g., Mirwis, 2011) and the main subject of this study. (See extended explication in Chapter 2.)

In general, evidence of concurrent validity was found as expected among the various instruments as well as across the multiple outside research studies that have been performed on the ABC and the ABC-C. For instance, Kaat et al. (2014) found evidence of divergent validity in an ASD sample, consisting of children between ages two and 18 years rated by parents, for the five ABC-C subscales when compared to the Vineland Adaptive Behavior Scales, Second Edition (VABS-II; Sparrow et al., 2005) Adaptive Behavior composite. Correlations ranged

from negative negligible (-.05 for Inappropriate Speech) to mildly negative (-.33 for Lethargy/Social withdrawal), with a median negative correlation of -.22. Relative to the Child Behavior Checklist (CBCL; Achenbach & Rescorla, 2001) form for ages six to 18 years old, convergent correlations were .43 between the ABC-C Lethargy, Social Withdrawal subscale and the CBCL Internalizing Problems score; .64 between ABC-C Irritability and CBCL Externalizing Problems score; and .58 between ABC-C Hyperactivity and CBCL Externalizing Problems score. Divergent relationships were reflected in correlations all less than .40 (most less than .30) between the CBCL Internalizing or Externalizing Problems scales with all other ABC-C subscales (see Kaat et al., 2014).

From a discriminant perspective, the ABC-C test authors highlight the analyses with the original ABC, which was found to yield significant mean differences between groups of subjects with intellectual disabilities who do and do not take psychotropic medications (e.g., antipsychotics, hypnotics, anticonvulsants, antihistamines, antidepressants; Aman & Singh, 2017; Aman et al., 1985b). According to Aman and Singh (2017) these findings provide further evidence of construct validity, as the ABC (and ABC-C) appears to be sensitive to differences between subjects who are taking medication (scoring higher on average, presumably with more extreme presenting externalizing and internalizing behaviors) and those who are not. From a treatment sensitivity perspective, the ABC-C has also been shown to be effective in documenting significant changes and differences, as an outcome measure, in behavioral intervention studies (Aman & Singh, 2017, p. 33).

Criterion-related relationships were assessed between the original ABC and direct behavioral observations (Aman et al., 1985b). Graduate students observed a group of 36 individuals in an institution using 10-second time intervals, for one hour total, in 15-minute

blocks (before, during, and after dinner). They recorded the subjects' behavior frequencies using categories consistent with the behaviors found in the ABC subscales (i.e., crying/irritability, self-injury, withdrawal/apathy, stereotypy, noncompliance, gross body movements, off-task behavior, repetitive speech, and repetitive vocalizations) with raters unaware of any of the individuals' previous scores on the ABC—as rated independently by institutional nurses (Aman et al., 1985b). Average agreement among raters was 91.3% (Aman & Singh, 2017; Aman et al., 1985b). Observed subjects were then assigned into either a "high" score group or a "low" score group depending upon whether their ABC subscale scores fell at least one standard deviation above or below the mean. The mean levels of the high and low groups for each of the different observation categories were then compared. Results showed statistically significant differences between the groups for the withdrawal/apathy, stereotypy, noncompliance, gross body movements, off-task behavior, and repetitive speech categories (Aman & Singh, 2017; Aman et al., 1985b). Nonsignificant results were found between the high and low groups on the crying/irritability, self-injury, and repetitive vocalization categories (Aman & Singh, 2017; Aman et al., 1985b). Aman and Singh (2017) attributed the non-significant findings between the low and high groups on the crying/irritable and self-injury categories to the low frequency and high variability of the behaviors represented in these categories. The authors also attributed the nonsignificant findings between the low and high groups on the repetitive vocalizations category to raters only rating intelligible speech rather than vocalizations that included sounds other than words (Aman & Singh, 2017). Overall, Aman and Singh (2017) concluded that this study provided further support for the ABC's construct validity as the more extreme cases established by independent, direct behavioral observations also tended to differ according to the nurses' ABC ratings.

Data analysis for study one. Analyses for study one were performed using several statistical programs. These programs included SAS Version 9.4 (SAS Institute Inc., 2013) and SPSS Version 25 (IBM Corp, 2017) along with an R programming language plugin for SPSS (Basto & Pereira, 2012; R Core Team, 2013).

SPSS Version 25 was used as the primary data management system for inputting item data from the ABC-C. Descriptive statistics were calculated using SPSS Version 25. The SPSS R plugin was used to generate the inter-item polychoric correlation matrix (for polychoric correlation, see Pearson [1900]) for the ABC-C, conducting a parallel analysis, and for deriving Cronbach's alpha, and ordinal alpha (Zumbo, Gadermann, & Zeisser, 2007) coefficients. SAS Version 9.4 was used to run the EFA using the ABC-C inter-item polychoric correlation matrix, generated from the SPSS R plugin, as input.

Pre-analysis data cleaning and missing data. For study one, data cleaning procedures as articulated by Osborne and Banjanovic (2016) were followed. Missing data were expected to be rare—given the procedures in place for catching and fixing missing ratings. However, in instances where missing ratings did occur, expectation-maximization (Allison, 2002) was used. The frequency of missing item data was not high enough to warrant bias analyses concerning missing data (e.g., evaluating data for missing completely at random, missing at random, etc.).

Data matrix sufficiency for factoring. For study one, the input matrix contained correlations rather than covariances. Given that the ABC-C item data are ordinal in nature, a polychoric correlation matrix was used instead of a Pearson correlation matrix (Holgado-Tello, Chacón-Moscoso, Barbero-García, & Vila-Abad, 2010). Pearson correlations would likely undervalue the strength of the relationships between ordinal rating variables and bias factor loadings. Based upon previous EFAs of the ABC-C with an ASD sample (i.e., Brinkley et al.,

2007; Kaat et al., 2014; Mirwis, 2011) which had variable/indicator to factor ratio solutions between 58:4 and 58:7 and using the moderate to high prior communality estimates reported by Mirwis (2011; M = .744, ranging from .534 to .918) as a guide, the sample size n = 300 cases for the present study was likely sufficient to confidently assess the factor structure of the ABC-C (see MacCallum et al., 1999, Table 1, p. 93).

The Bartlett's Test of Sphericity (Bartlett, 1950) was used to assess whether the observed correlation matrix is significantly different from what would be expected by chance from an identity matrix (Pedhazur & Schmelkin, 1991). Additionally, because an EFA was used in this study—with its emphasis on common rather than total variance (O'Rourke & Hatcher, 2013)—it was helpful to determine whether the amount of common variance present reflected a sufficient likelihood of common factors being present in the inter-variable correlation matrix (Kaiser, 1970; Kaiser & Rice, 1974). For this purpose, the Kaiser-Meyer-Olkin (KMO; Kaiser, 1970; Kaiser & Rice, 1974) test was performed on the correlation matrix. Following criteria outlined by Kaiser and Rice (1974), a KMO value above .8 would indicate a very suitable data matrix and values below .5 would indicate a matrix not acceptable for an EFA. More specifically, Kaiser and Rice (1974) characterized KMO values in the .90s as "marvelous," values in the .80s as "meritorious," values in the .70s as "middling," values in the .60s as "mediocre," values in the .50s as "miserable," and values < .50 as "unacceptable" (p. 112).

Extraction methods. It was anticipated, based on previous EFAs with the ABC-C with the ASD population (e.g., Mirwis, 2011), that the data would violate univariate and multivariate normality. Under such conditions, principle axis factoring (PAF) is the more robust extraction method compared to maximum likelihood (ML), which strongly assumes normality/multivariate

normality (Floyd & Widaman, 1995; Osborne & Costello, 2005). Therefore, for study one the PAF method was used as the primary extraction method.

Number of factors to retain. For study one, a combination of the Guttman-Kaiser criterion (i.e., minimum eigenvalue greater than one criterion), the scree test, parallel analysis, and the MAP test, were used to help determine the most appropriate number of factors to retain– with interpretability of the factors guiding final retention decisions. For the scree test, factor solutions were analyzed based upon the perceived elbow(s) in the scree plot. Per the recommendations for parallel analysis made by Glorfield (1995), factors were considered for retention if their obtained eigenvalues exceeded the 95th percentile of the random data matrix eigenvalues. With regard to the MAP test, per recommendations by Osborne and Banjanovic (2016), common variance was partialed out for each successive factor until only unique variance was left (i.e., common variance is reduced to a minimum).

Rotation. For study one an oblique rotation was used as it was expected that factors would be correlated based upon previous EFAs (e.g., Kaat, et al., 2014; Mirwis 2011) with the ABC-C. Experts also contend that oblique rotations are equally effective for both correlated and uncorrelated factors (Fabrigar & Wegener, 2012; Osborne, 2015). As a result, a direct oblimin rotation was used as the primary method.

Interpreting the solution. For study one, factor loadings < .30 were considered significant (Beavers et al., 2013). Items found to load between .30 and .45 were considered significant though questionably substantive. Using the criteria outlined by Comrey and Lee (as cited in Pett et al., 2003), factor loadings $\geq$ .45 were considered fair, $\geq$ .55 were considered good, $\geq$ .63 were considered very good, and $\geq$ .71 were considered excellent. Crossloadings (i.e., items that load at $\geq$ .30 on more than one factor) were examined to determine which factor loading best

reflected the underlying concept (Osborne & Costello, 2005). With these rules in place, factor naming then occurred. Pett et al. (2003) stated that the highest loaded item, especially if it is ≥ .90, should offer a strong indication of the essence of that factor. If the highest loadings are ≤ .60, then interpretation might be less robust (Pett et al., 2003). Thus, factor naming for this study took into account the recommendations provided by Pett et al. (2003), relevant symptomology and associated features in the ASD population, and prior theoretical constructs articulated for the ABC-C. Finally, in order to provide greater confidence in factor solutions for this study, factor solutions and their subsequent factor names were independently interpreted by four qualified researchers and consensus was established.

Internal consistency. For study one, internal consistency reliability estimates were measured for the original ABC-C scales. To measure internal consistency reliability in this study, both ordinal alpha and Cronbach's original coefficient alpha were used. Ordinal alpha was chosen to be the primary estimate of internal consistency reliability, because it replaces the Pearson correlations with polychoric correlations in the original alpha formula (Gadermann, Guhn, & Zumbo, 2012). Thus, it is theoretically similar to Cronbach's alpha, but is better suited to estimating internal consistency in the context of ordinal item scales (Gadermann et al., 2012). Cronbach's coefficient alpha estimates were also generated in order to maintain a common standard for comparison with previous studies, as many did not use ordinal alpha. The criteria provided by Murphy and Davidshofer (as cited in Sattler, 2008) were used to evaluate the strength of reliability estimates. Estimates were considered as having very low or very poor reliability (.00 to .59), low to poor reliability (.60 to .69), moderate or fair reliability (.70 to .79), moderately high or good reliability (.80 to .89), or high or excellent reliability (.90 to .99). However, adequate reliability is ultimately relative to the intended purpose for which a particular

scale or score is ultimately used. Nunnally (1978) suggested a minimum reliability of .70 for research purposes.

Comparing five-factor solutions. An interpretable five-factor solution in the present study was compared to the five subscales and associated constructs currently endorsed in the ABC-C2 manual by the test authors (Aman & Singh, 2017). Factor constructs were initially qualitatively compared by assessing the similarities and dissimilarities between the factor names for the derived constructs. Next, the highest loading items (that are key to defining and naming the factors) were compared to determine whether they were similar between the different solutions. Finally, a percentage of overlapping items between the factors from the obtained five-factor solution and those from the five-subscale structure currently endorsed by the authors of the ABC-C were assessed.

Study Two: CFA

Research question, rationale, and hypotheses.

Research question 5. *How does the factor solution generated in a sample of individuals with ASD rated by special education staff members for the ABC-C compare in terms of absolute and relative fit to previous ABC-C factor models found in ASD samples or proposed for use with individuals with ASD?*

Research rationale and hypotheses 5a and 5b. Kaat et al. (2014) found relative parity amongst the factor models they tested (i.e., the Aman et al., 1985a, five-factor model; the Brinkley et al., 2007, four-and-five factor models; the Brown et al., 2002, four-factor model; the Sansone et al., 2012, six-factor model), all of which resulted in a generally marginal fit (i.e., RMSEA ranged from .081 to .12, SRMR ranged from .09 to .12). The authors concluded that because no specific model could be clearly distinguished as the best fit amongst the models they

tested with their validation sample, the original Aman et al. (1985a) structure should be maintained for individuals with ASD. It has been argued in the present study that the factor solution retained through EFA in study one will be the most robust when compared to the existing factor models for the ABC-C, as a result of the thoroughness (i.e., using the most effective factor selection criterion methods, analyzing a range of potential factor solutions) of the analyses performed. Consequently, two hypotheses will be tested.

First, it is hypothesized that the ABC-C factor model determined in the study one EFA, when appropriately constrained for CFA (e.g., with parameters for theoretically non-loading items fixed to zero), will adequately fit the ABC-C variance-covariance matrix of the second ASD sample. This will be determined using a combination of absolute, complexity-adjusted, and relative fit indices (i.e., weighted least squares mean and variance adjusted estimator [WLSMV; Muthén & Muthén, 1998-2017], adjusted chi square [χ^2], Root Mean Square Error of Estimation [RMSEA], Comparative Fit Index [CFI], Tucker-Lewis Index [TLI], and Standard Root Mean Square Residual [SRMR]). Second, the ABC-C factor model determined in the study one EFA, when appropriately constrained for CFA (e.g., with parameters for theoretically non-loading items fixed to zero), will demonstrate a better fit to the second ASD sample ABC-C variance-covariance matrix than previous ABC-C factor models found in ASD samples or proposed for use with individuals with ASD. Because of the non-nested nature of the CFA models to be compared, Akaike's Information Criterion (AIC) and the Bayes Information Criterion (BIC) fit indices (available through the Mplus robust maximum likelihood [MLR] estimator) will be used for this purpose. Though the Mplus WLSMV estimator does offer an adjusted likelihood ratio test (i.e., DIFFTEST) to compare nested models, this test cannot be used to assess differences between non-nested models. In addition, the WLSMV estimator does not allow for the

calculation of AIC and BIC indices. Thus, AIC and BIC will be estimated using the MLR estimator.

Table 13. *Summary of Study Two Research Questions*

Research Question Number	Research Question	Hypothesis	Analysis	Method(s)
5	How do the existing factor solutions for the ABC-C compare in terms of absolute and relative fit?	5a: The model generated in Study one will adequately fit the matrix of the second ASD sample	χ^2, SRMR, RMSEA, CFI, TLI for evaluating adequacy of fit	Confirmatory Factor Analysis
		5b: The model generated in Study one will demonstrate a better relative fit to the matrix of the second ASD sample compared to previous models of the ABC-C with an ASD sample	Primarily AIC and BIC for direct comparison of non-nested models	Confirmatory Factor Analysis

Study two sample demographics. The sample for study two consists of 243 ASD cases. Sample participants include 80.2% males (*n* = 195) and 19.8% females (*n* = 48), ranging in age from 2.95 to 21.15 years (*M* = 10.79, *SD* = 4.53; See Table 14). Note that the obtained sample male-to-female ratio is similar to the best available population-level estimate of the ratio in ASD of 4.5:1 (see Baio et al., 2018). Ethnic identification includes 77.0% white/non-Hispanic (*n* = 187), 12.8% black/African-American (*n* = 31), 4.5% Hispanic (*n* = 11), 1.2% Asian American (*n* = 3), 1.6 % other (*n* = 4), 2.9% unknown (*n* = 7). Socioeconomic data is the same as in study one.

Table 14. *Demographic Characteristics of Study Two Sample*

	Sample *N* (%)	Mean (*SD*)	Range
Participant Gender			
Male	195 (80.2)		

Table 14 (cont'd)			
Female	48 (19.8)		
Participant Race/Ethnicity			
White/Non-Hispanic	187 (77.0)		
Black/African-American	31 (12.8)		
Hispanic, No Race Specified	11 (4.5)		
Asian American	3 (1.2)		
Other	4 (1.6)		
Unknown	7 (2.6)		
Participant Age	243 (100)	10.79 (4.53)	2.95-21.15
Participant Deviation Quotient Score	242 (99.6)	56.69 (18.71)	12-123
Unknown	1 (.4)		

Note: All cognitive scores were set to a deviation quotient (DQ) metric (i.e., normative mean of 100, standard deviation of 15) in order to allow for some limited comparability of participants' cognitive scores

Cognitive deviation quotient scores (DQ) ranged from 12 to 123 (M = 56.69, SD = 18.71), with 78.1% of the sample with DQ scores $\leq$ 70 (i.e., at least two standard deviations below the mean), and 93.8% $\leq$ 85 (i.e., at least one standard deviation below the mean). Nonetheless, like study one, all individuals included in the sample in this study had substantial functional impairments in the cognitive, social, or communication domains (or some combination of the three) severe enough to warrant participation in special education classrooms.

The sample for study two contained 179 cases (74%) also found in study one, with 64 cases (26%) not overlapping. The data from the 179 overlapping cases between study one and study two were collected at different time points and ratings were completed by different special education staff members. The average time between ratings for the same case across the two studies was 879 days (2.41 years).

Data analysis for study two. Analyses for study two were performed using two statistical programs in order to carry out the various required calculations. These programs included SPSS Version 25 (IBM Corp, 2017) as well as Mplus Version 8.2 (Muthén & Muthén, 1998-2017).

SPSS Version 25 was used as the primary data management system for inputting item data from the ABC-C. Descriptive statistics were calculated using SPSS Version 25. Mplus Version 8.2 was used to assess the factorial validity of first-order confirmatory factor analytic models for the ABC-C. (The Mplus WLSMV estimator was used as the primary estimation strategy given the ordinal and non-normal ABC-C item data.) The primary model of interest was based on the study one EFA results, but this model was also compared to several others from the literature based on findings in other ASD samples or suggested for use with ASD. Information criteria indices (AIC and BIC), used for cross-model comparisons, were derived using the robust maximum likelihood (MLR) estimator in Mplus.

Pre-analysis: Data cleaning and missing data. For study two, data cleaning procedures were the same as for study one. Like study one, missing data were expected to be rare. As such, expectation-maximization (Allison, 2002) was used to estimate and replace any missing values. As in study one, the frequency of missing item data was not high enough to warrant bias analyses concerning missing data (e.g., missing completely at random, missing at random, etc.).

Data matrix sufficiency for factoring. Harrington (2009) asserts that although there are disagreements as to the required sample size for a CFA, "the larger the sample size, the better for CFA" (p. 45). According to MacCallum et al. (1999), the same ratio of variables to factors with moderate to high communality estimates acceptable for EFA (see study one) should be acceptable for CFA as well, meaning a sample of size between 100 and 200 would likely be sufficient to achieve convergent solutions for anticipated ABC-C structures. Yet, in a Monte Carlo study focused on sample size by Muthén and Muthén (2002), a sample size of 150 was sufficient when data were normally distributed, but a sample of 265 was necessary for data that were non-normal. The sample size in the present study (n = 243) is of moderate size and item

distributions are anticipated to be non-normal in an ASD sample. These issues were taken into account when deriving conclusions.

In order to choose the most appropriate estimation method for the CFA, the dataset needed to be examined to determine the type of distribution the data follow (i.e., multivariate normal or multivariate non-normal). According to Curran, West, and Finch (1996), if univariate skewness or kurtosis is substantial (i.e., skewness > 2, kurtosis > 7) then it is likely that the multivariate distribution will be non-normal as well. Performing probability-probability (P-P) plot analyses in SPSS revealed consistent long-tails among the item data indicating a potential non-normal distribution. Further, skewness and kurtosis statistics revealed three items with a skewness > 2 and no items with a kurtosis > 7. Though only three items appeared sufficiently non-normal to be of concern according to the criteria by Curran et al. (1996), the ordinal nature of the item data and non-normal visual appearance of most of the item distributions suggested the need for a robust estimation procedure.

As noted previously, the four-point scale for ABC-C items is ordinal in nature. In addition, experience with prior data sets and analyses of other measures from ASD samples that require more intensive supports (e.g., Mirwis, 2011) suggested that the item data would be non-normal. Given the ordinal nature of the data, a robust diagonally-weighted procedure was most appropriate. Within Mplus, the weighted least squares mean and variance adjusted estimator (WLSMV) addressed this issue well (DiStefano & Morgan, 2014). However, more extreme non-normality in the data or model misspecification can impact standard errors and statistical power (see DiStefano & Morgan, 2014). Despite these issues, DiStefano and Morgan (2014) noted that a) average RMSEA and CFI values did not appear to be sensitive to differences (e.g., in normality) in their simulation study conditions involving diagonally-weighted procedures with

ordinal data and, b) the Mplus WLSMV procedure appeared preferable to LISREL's diagonally-weighted estimation option in the presence of moderate non-normality, few scaling categories, and smaller sample sizes. It should be noted, however, that their study conditions all assumed a correctly specified model.

Model specification. In CFA, model specification involves detailing the specific models that are to be tested (Harrington, 2009). This entails specifying the observed and latent variables, the unique variances (i.e., the error variance in each item not accounted for by the latent factor[s]), the correlations between factors, and the directional paths from factors (latent variables) to items (observed variables). A graphical structure is used to denote the paths and parameters for these relationships. Observed variables (i.e., the specific items) are represented by rectangles and latent variables (i.e., the factors) are represented by ovals. Directional paths between latent and observed variables are represented by single-headed arrows, and correlations between latent variables are represented by double-headed arrows (Harrington, 2009). Arrows from latent to observed variables denote latent variable constructs affecting observed variables. Factor loadings for each variable are also provided which are the equivalent of regression coefficients predicting the observed variables from the unobserved factors (Harrington, 2009). Each observed variable has a direct path arrow pointing to it from an associated error term. This error term, in the case of observed variables, reflects measurement error (i.e., a combination of random error and unique variance not accounted for by factors). These error terms (also referred to as residuals in Mplus) usually have their paths fixed to 1.0 (in order to provide a scale for the error term based on the observed variable) and have their variances freely estimated (Byrne, 2012).

For the CFA in study two, multiple models were assessed. The model derived and settled upon in the EFA in study one was of primary interest. It was assessed along with the models derived from previous factor analyses of the ABC-C. These included the four-and five-factor models from Brinkley et al. (2007) from an ASD sample with parent raters, and the seven-factor model from Mirwis (2011), from an ASD sample with special education staff raters. The five-factor model derived by Kaat et al. (2013) from an ASD sample with parent raters was not included. Instead the original five-factor model from Aman et al. (1985a) was used, which was derived from an ID population rated by institutional staff members. Per advice from Aaron Kaat (A. Kaat, personal communication, January 30, 2018), the Aman et al. (1985a) model was very similar to the Kaat et al. (2013) model, and the differences between them are not likely to be meaningful and may be mostly resulting from sampling error. Additionally, the six-factor model derived in Sansone et al. (2012) from a Fragile X population rated by caregivers was also assessed given the strong model fit reported in their study and the known co-morbidity between ASD and Fragile X (e.g., Abbeduto, McDuffie, & Thurman, 2014). However, because Sansone et al. (2012) used parceling in their model it could not be directly compared to the other models that used all 58 items as observed variables. See Appendix A, B, C, D, E, and F for Model 1 and Model 2 (Brinkley et al., 2007), Model 3 (Mirwis, 2011), Model 4 (Aman et al., 1985a), Model 5 (Sansone et al., 2012), and Model 6 (the study one, nine-factor model).

Model identification. Model identification refers to setting two important conditions in a CFA model: a) ensuring that the degrees of freedom (*df*) in the model are > 0, and b) providing a scale for each latent variable in the model (i.e., establishing a unit of measurement for the latent variables; Harrington, 2009). In order for both the model parameters to be estimated in the CFA, and for the fit of the model to be determined, there must be more unique information elements in

the variance-covariance matrix (i.e., total number of covariances and variances in the matrix) than there are unknown parameters to be estimated in the factor model. If there are more unknown parameters to be estimated than there are elements in the variance-covariance matrix, then a situation arises where the model cannot be properly estimated due to insufficient degrees of freedom (*df*). The *df* represent the difference between the total information elements available in the inter-item variance-covariance matrix and the unknown parameters to be freely estimated. Models can be underidentified (i.e., when there are more freely estimated parameters than there are unique information elements in the variance-covariance matrix, resulting in $df < 0$), just-identified (i.e., the number of unknown parameters to be estimated in the model equals the number of elements in the variance-covariance matrix, resulting in 0 *df*), or overidentified (i.e., where there are fewer unknown parameters to be estimated in the model than there are elements in the variance-covariance matrix, resulting in $df > 0$; Harrington, 2009). All models evaluated in study two were overidentified.

Scaling latent variables is necessary in CFA because factors have no inherent scale of their own; meaningful units of measurement for latent variables do not exist prior to identification (Harrington, 2009). According to Byrne (2012) there are three possible ways to provide a scale for latent variables: a) units of measurement can be set for a factor relative to one of its observed item variables, typically accomplished by fixing the factor loading path to 1.0 for that observed variable (i.e., the reference variable method); b) factor variances can all be set to 1.0, thereby allowing all factor loadings to be freely estimated using factor variance units (i.e., the fixed factor method); or c) constraining factor loadings and indicator intercepts (i.e., effects coding). According to Byrne (2012), there are debates in the literature regarding the most effective method as each has its strengths and weaknesses. For the CFA in study two, the fixed

factor method was used to allow for all factor loadings to be freely estimated and to enhance the interpretability of inter-factor covariances—which can be interpreted as correlation coefficients when factor variances are standardized.

Model estimation. The core purpose of CFA is to determine whether a particular hypothesized model is congruent with or "fits" the variance-covariance data (Harrington, 2009). To accomplish this all parameters in the CFA model (e.g., factor loadings and error variances for each item) need to be estimated to determine the quality of the data fit. The estimation process is iterative in that calculations are performed repeatedly with increasing precision until the convergence criterion is reached and the model is estimated as precisely as possible (Harrington, 2009). There are several different methods that can be used to estimate parameters in a CFA—with each method more or less appropriate based upon the nature of the data.

For study two a weighted least squares mean and variance adjusted (WLSMV; Muthén, 1993; Muthén, du Toit, & Spisic, 1997; Muthén & Muthén, 2017) approach with the polychoric correlation matrix and sample estimated asymptomtic covariance matrix as input was used given the fact that the item data are both ordinal and non-normal. This is similar to the diagonally-weighted least squares (DWLS) method found in LISREL (Jöreskog and Sörbom as cited in Kaat et al., 2007) that Kaat et al. (2014) used in their CFA analysis of the ABC-C. WLSMV was adapted from the weighted least squares (WLS) estimation method (DiStefano & Morgan, 2014). In WLSMV a diagonal weight matrix is used along with "robust-standard errors and a mean-and variance adjusted $\chi^{2,}$ test statistic" (Muthén & Muthén, in Brown, 2006, p. 388).

Model fit. Once the estimation method is run on the hypothesized model(s), it is necessary to assess how well the models fit the data. There is no consensus on exactly which fit indices to use (Brown, 2006; Iacobucci, 2010; Jackson, Gillaspy, & Purc-Stephensonm 2009)

and what exact values signify a satisfactory fit (e.g., Brown, 2006; Hu & Bentler, 1999). As such, Brown (2006) recommends that researchers use at least one fit index from each of three different fit index categories: absolute fit indices, fit adjusting for model parsimony, and comparative (or incremental) fit indices. Jackson et al. (2009) stated that although there is not a universally accepted number of indices to use they recommend that at least a chi-square value with degrees of freedom and probability value, an incremental fit index (a.k.a., a comparative fit index), and a residuals-based measure (e.g., RMSEA) should be included.

Absolute fit indices examine whether the predicted variance-covariance matrix is equivalent to the sample variance-covariance matrix (Harrington, 2009). In this study the WLSMV-adjusted Chi-Square (χ^2) absolute fit index and the Standardized Root Mean Square Residual (SRMR) were used. Chi-square examines whether the model of interest satisfactorily replicates the variances and covariances found in the sample data (Brown, 2006). A statistically significant χ^2 value ($\alpha < .05$**)** indicates that the model does not entirely fit the data (Brown, 2006). As Brown (2006) pointed out, this statistic is common in CFA research but infrequently used on its own given the fact that its result is vulnerable to issues regarding sample size (both large and small), non-normal data, and the fact that the core hypothesis of the index is highly restricted. The SRMR examines the average differences between the correlations found in the data matrix and the correlations that are predicted by the hypothesized model (Brown, 2006; Harrington, 2009). Thus, the SRMR outcome is a measure of how discrepant the model is from a perfect fit of 0. Values of the SRMR statistic can range from 0 to 1. Hu and Bentler (1999) recommend a cutoff value of "close to .08" for the SRMR (p. 27).

Parsimony correction indices are similar to absolute fit indices except that with parsimony correction indices, the number of *df* are taken into consideration in a particular way

(i.e., incorporating an increasing fit penalty as the number of freely estimated parameters increases; Brown, 2006). This means that, all other things being equal, more complex models are less likely to result in a good fit using these indices (Harrington, 2009). In this study the Root Mean Square Error of Estimation (RMSEA; Steiger, 2016; Steiger & Lind, 1980), the Akaike's Information Criterion (AIC; Akaike, 1987), and the Bayes Information Criterion (BIC; Rafferty, 1993) parsimony correction indices were used. The RMSEA is deemed an "error of approximation" because it estimates the degree of model mis-fit relative to the population (Brown, 2006, p. 83). It was selected for this study because it is not greatly affected by sample size. As Brown (2006) explained, a perfect fit for RMSEA is 0, and the statistic is assessed based upon how close to 0 the model fit occurs. RMSEA values articulated by Browne and Cudeck (1993) will be used. This includes values $\leq$ .05 considered a "close fit," values > .05 and $\leq$ .08 considered "reasonable" fit, and values $\geq$ .10 would signify a model that should not be used (p. 144). Of note, Hu and Bentler (1999) maintain an RMSEA cut-off number of approximately .06. Additionally, MacCallum, Browne, and Sugawara (1996) urge the use of confidence intervals when using fit indices. Mplus provides a 90% confidence interval for RMSEA values (Byrne, 2012).

The AIC and BIC parsimony correction indices were also chosen for this study because they enable a comparison to be made between two non-nested models on the same set of data (Byrne, 2012). The various models that were tested in this study were non-nested. All but one of the models (Sansone et al., 2012) were based on the same numbers of observed variables but some models differed in terms of numbers of factors and combinations of variable loadings on the factors between each model. Like the RMSEA, the AIC and the BIC allocate penalties with regard to model fit based on model complexity. The BIC allocates a larger penalty than the AIC

and therefore is more likely to favor more parsimonious models over more complex models. As Harrington (2009) explains, because the AIC and BIC are used specifically to compare different models, there are no quantifiable parameters to determine what constitutes a satisfactory model fit. As such, the lower the value of the AIC and BIC, the better the fit of the hypothesized model—with the advantage given to the model with the lower value (Byrne, 2012). (As noted previously, AIC and BIC values needed to be estimated through another Mplus estimation procedure [e.g., a robust maximum likelihood variant], as WLSMV does not produce AIC and BIC estimates.)

Comparative (or incremental) fit indices assess the fit of a hypothesized model relative to a restricted, nested model (i.e., a parent model that encompasses another model; Brown, 2006). The restricted model in a comparative fit index has the covariance between observed variables removed so that the variables remain independent (Brown, 2006). Thus, with comparative fit indices, a hypothesized model is compared to a simpler version of the model where there are no correlations between variables (Brown, 2006; Iacobucci, 2010). In the present study the Comparative Fit Index (CFI; Bentler, 1990) and the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973) were chosen. Like the RMSEA, the CFI maintains a range of potential values from 0 to 1 (Brown, 2006). According to Brown (2006) CFI values > or close to .95 are considered reasonably well fitting. Brown (2006) indicated that there is a range between .90 and .95 that should be considered "marginal," but that one must ultimately judge the fit based upon the outcomes of the other indices as well and not just in isolation (p. 87). Hu and Bentler (1999) recommend a cutoff number close to .95. The TLI is different from the CFI in two distinct ways. Unlike the CFI, it is considered a nonnormed index, meaning that its values can range from 0 to

above 1 (Byrne, 2012) and it includes a penalty for more complex models. Similarly to CFI, values closer to 1 are considered an acceptable model fit (Brown, 2006).

Model modification. Hypothesized models do not always result in acceptable fit. This can occur for multiple reasons, but ultimately in a CFA, one has the opportunity to examine the modification indices for a model to determine what modifications could improve its fit (Harrington, 2009). However, this involves going back into exploratory mode and risking model modifications that may have been suggested due to sampling error. Thus, any such post hoc model modifications would need to be confirmed through a CFA in another sample (Sörbom, 1989). Given the purely confirmatory nature of study two, model modification did not occur. The various hypothesized models were tested only as originally hypothesized to assess the adequacy of each one—and determine which model offered the best fit to the data.

CHAPTER 4: RESULTS

Study one involved analyzing the factor structure of the of the Aberrant Behavior Checklist–Community (ABC-C, Aman & Singh, 2017) with a sample of individuals with ASD using a polychoric correlation matrix for an exploratory factor analysis (EFA) with principal axis factoring (PAF) and a direct oblimin rotation. Internal consistency reliability estimates were obtained using ordinal alpha, as the primary estimate, and Cronbach's alpha, in order to provide a standard of comparison with other studies. Study two focused on examining the absolute fit, fit adjusting for model parsimony, and comparative fit of the factor structure of the ABC-C generated in study one against other existing models of the ABC-C using a confirmatory factor analysis (CFA).

Analysis

Results are reported relative to each research question. Given the nature of the EFA analysis of study one, research questions 1 through 3 were answered using overlapping outcome data. Thus, outcome data will be reported in the initial questions and then referenced as needed in subsequent questions.

Study One

Data cleaning and missing data. The dataset for study one was scanned for missing values before performing the EFA. Results showed less than 1% of the 300 cases had missing values. An expectation-maximization (i.e., a mean item replacement; Allison, 2002) was used so that the cases with missing data could be included in the analyses. A more intensive multiple imputation process was deemed unnecessary.

Data matrix sufficiency for factoring. The mean and standard deviation of each item used in the data set for the EFA can be found in Table 15. The inter-item polychoric correlation

matrix can be found in Appendix G. This matrix includes estimates of how each item relates to all others in the dataset. Prior communalities are located on the diagonal of the polychoric correlation matrix. Of note, because the polychoric matrix was found to be non-positive definite (i.e., with eigenvalues < 0), the maximum correlation method was used to estimate prior communalities (i.e., communalities estimated before the oblique rotation).

Table 15. *Descriptive Statistics of the EFA Dataset*

				Percent of Sample Responses for Each Item Scale Point (N = 300)			
Item #	Stem	Mean	Standard Deviation	0 Not at all a problem	1 The behavior is a problem but slight in degree	2 The problem is moderately serious	3 The problem is severe in degree
1	Excessively active at home, school, work, or elsewhere	0.95	1.025	45.7	23.0	22.0	9.3
2	Injures self on purpose	0.69	1.019	62.3	16.0	12.0	9.7
3	Listless, sluggish, inactive	0.49	0.832	68.3	18.3	9.0	4.3
4	Aggressive to other children or adults (verbally or physically)	0.97	1.074	46.7	22.0	19.0	12.3
5	Seeks isolation from others	0.73	0.946	54.0	27.3	10.7	8.0
6	Meaningless, recurring body movements	1.09	1.092	40.0	26.3	18.3	15.3
7	Boisterous (inappropriately noisy and rough)	1.12	1.121	40.0	25.3	17.3	17.3
8	Screams inappropriately	1.04	1.110	44.7	22.0	18.3	15.0
9	Talks excessively	0.63	0.974	64.3	16.0	11.7	8.0
10	Temper tantrums / outbursts	1.36	1.135	30.3	25.3	22.0	22.3
11	Stereotyped behavior; abnormal, repetitive movements	1.33	1.128	29.7	30.3	17.3	22.7
12	Preoccupied; stares into space	1.10	1.070	38.7	27.0	20.3	14.0
13	Impulsive (acts without thinking)	1.29	1.113	31.7	27.0	21.7	19.7
14	Irritable and whiny	0.98	0.954	38.3	33.3	20.3	8.0
15	Restless, unable to sit still	1.17	1.075	36.3	25.0	24.3	14.3
16	Withdrawn; prefers solitary activities	0.91	1.024	46.0	27.7	15.3	11.0
17	Odd, bizarre in behavior	1.08	1.117	42.7	23.0	18.3	16.0

Table 15 (cont'd)

18	Disobedient; difficult to control	1.02	1.013	39.7	29.7	20.0	10.7
19	Yells at inappropriate times	1.03	1.069	42.7	25.0	19.3	13.0
20	Fixed facial expression; lacks emotional responsiveness	0.57	0.829	62.0	22.7	12.0	3.3
21	Disturbs others	1.18	1.002	30.0	34.7	22.7	12.7
22	Repetitive speech	0.86	1.035	50.7	23.3	15.3	10.7
23	Does nothing but sit and watch others	0.34	0.688	75.7	16.7	5.3	2.3
24	Uncooperative	0.96	0.930	38.7	32.7	22.3	6.3
25	Depressed mood	0.28	0.629	80.0	13.7	4.7	1.7
26	Resists any form of physical contact	0.37	0.659	71.7	21.7	5.0	1.7
27	Moves or rolls head back and forth repetitively	0.34	0.725	79.0	10.7	8.0	2.3
28	Does not pay attention to instructions	1.20	0.953	25.7	40.7	22.0	11.7
29	Demands must be met immediately	0.91	1.024	47.0	24.7	18.3	10.0
30	Isolates himself/herself from other children or adults	0.69	0.951	59.0	20.0	14.3	6.7
31	Disrupts group activities	1.13	0.986	32.7	31.3	26.0	10.0
32	Sits or stands in one position for a long time	0.32	0.697	78.7	13.3	5.3	2.7
33	Talks to self loudly	0.63	0.954	64.3	14.7	14.7	6.3
34	Cries over minor annoyances and hurts	0.82	0.980	50.3	26.0	15.3	8.3
35	Repetitive hand, body, or head movements	1.09	1.115	41.0	26.3	15.7	17.0
36	Mood changes quickly	1.10	1.072	37.7	29.3	18.0	15.0
37	Unresponsive to structured activities (does not react)	0.57	0.837	61.7	23.7	10.7	4.0
38	Does not stay in seat (e.g., during lesson or training periods, meals, etc.)	0.86	0.982	47.3	28.0	16.0	8.7
39	Will not sit still for any length of time	0.71	0.931	55.3	24.3	14.0	6.3
40	Is difficult to reach, contact, or get through to	0.91	1.028	46.0	28.0	14.7	11.3
41	Cries and screams inappropriately	1.09	1.115	42.0	23.3	18.7	16.0
42	Prefers to be alone	0.79	0.968	51.7	26.0	14.3	8.0
43	Does not try to communicate by words or gestures	0.66	0.991	62.7	18.3	9.7	9.3
44	Easily distractible	1.35	1.057	26.0	31.7	24.0	18.3
45	Waves or shakes the extremities repeatedly	0.93	1.086	49.0	22.0	15.7	13.3
46	Repeats a word of phrase over and over	0.89	1.105	52.3	21.0	12.0	14.7

Table 15 (cont'd)

47	Stamps feet or bangs objects or slams doors	0.74	0.992	56.7	22.0	12.3	9.0
48	Constantly runs or jumps around the room	0.74	1.022	58.3	20.0	11.3	10.3
49	Rocks body back and forth repeatedly	0.52	0.897	69.0	16.0	8.7	6.3
50	Deliberately hurts himself/herself	0.68	1.030	63.7	15.0	11.0	10.3
51	Pays no attention when spoken to	0.91	0.934	39.7	38.3	13.3	8.7
52	Does physical violence to self	0.60	0.984	67.7	12.7	11.3	8.3
53	Inactive, never moves spontaneously	0.21	0.560	85.7	8.3	5.3	0.7
54	Tends to be excessively active	0.80	1.069	56.7	19.0	12.0	12.3
55	Responds negatively to affection	0.30	0.651	78.7	15.3	3.7	2.3
56	Deliberately ignores directions	0.87	0.924	43.0	33.3	17.0	6.7
57	Has temper outbursts or tantrums when he/she does not get own way	1.40	1.151	31.7	18.7	27.3	22.3
58	Shows few social reactions to others	0.90	0.963	43.0	32.7	15.7	8.7

To determine whether the data matrix was sufficient to perform an EFA, Bartlett's Test of Sphericity (Bartlett, 1950) and the Kaiser-Meyer-Olkin test of sampling adequacy (KMO; Kaiser 1970; Kaiser & Rice, 1974) were used. Bartlett's Test of Sphericity (Bartlett, 1951) was statistically significant ($\chi^2 = 14723.937$, $df = 1653$, $p < .000$). This indicates that the data matrix is unlikely to be an identity matrix because the correlations of the variables in the matrix are statistically different from 0. The KMO test of sampling adequacy (Kaiser 1970; Kaiser & Rice, 1974) was .941. According to the criteria outlined by Kaiser and Rice (1974) values above .8 indicate a suitable data matrix, with values in the .90s considered "marvelous" (p. 112). Results from this test show that the amount of common variance in the data matrix represents a reasonable probability that common factors will be present. Overall, results from both Bartlett's

Test of Sphericity (Bartlett, 1950) and the KMO test of sampling adequacy (Kaiser, 1970; Kaiser & Rice, 1974) establish that the data matrix is sufficient to perform an EFA.

The sample size of the polychoric data matrix was also analyzed according to the standards described in MacCallum et al. (1999). Communality estimates for the 58 items (*M* = .802, *Min* = .637, *Max* = .958) were considered high (i.e., values > .600). Additionally, the anticipated variable-to-factor ratio between 58:4 and 58:7 and a sample of 300 subjects, meets the standards of the percentages of admissible and convergent solution rates at 100% for sample sizes > 60. Therefore, according to the standards described in MacCallum et al. (1999), the 300-subject sample size used in this analysis is sufficient.

Research question 1*: Based upon ratings of a sample of individuals with ASD by special education staff, how many possible or likely interpretable ABC-C factors are available for retention consideration? Hypothesis: there will be between four and seven interpretable factors available for retention.* This was determined using Principal Axis Factoring (PAF), the Guttman-Kaiser Criterion (Guttman, 1954; Kaiser, 1960), the scree-test (Cattell, 1966), parallel analysis (Horn, 1965), and the minimum average partial test (MAP; Velicer, 1976).

Initial extraction. PAF was chosen based upon the assumption that the dataset would likely violate univariate and multivariate normality. PAF works by substituting the diagonal components of the correlation matrix with initial communality estimates (Osborne & Banjanovic, 2016). Initial communalities represent estimates of the variance in each item that is accounted for by all factors. The Guttman-Kaiser Criterion, scree test, parallel analysis, and the MAP test were used to decide how many possible factors would be available for interpretation. It is important to note that EFA analyses were performed on both SAS and SPSS with the R plugin. Slightly different formulas are used to calculate eigenvalues on each program resulting in

somewhat different, but very similar results. Eigenvalue estimates from SAS and SPSS will be provided for comparison where necessary.

The Guttman-Kaiser Criterion uses observed eigenvalues > 1 as the basis to determine how many factors to retain. Table 16 lists all of the observed eigenvalues generated from both SPSS and SAS. Both programs showed that possible factors one through eight > 1 eigenvalue. Thus, according to the Guttman-Kaiser Criterion an eight-factor solution should be retained because eight factors have eigenvalues > 1.

Table 16. *Eigenvalues for the Guttman-Kaiser Criterion*

Possible Factor	SPSS Observed Eigenvalues[a]	SAS Observed Eigenvalues
1	25.862	25.797
2	6.032	5.971
3	3.205	3.143
4	2.899	2.842
5	2.221	2.188
6	1.527	1.473
7	1.254	1.203
8	1.094	1.026
9	0.930	0.852
10	0.797	0.744
11	0.704	0.633
12	0.619	0.540
13	0.543	0.491
14	0.481	0.400
15	0.436	0.362
16	0.417	0.320
17	0.385	0.304
18	0.337	0.261
19	0.327	0.241
20	0.309	0.209
21	0.272	0.199
22	0.235	0.161
23	0.220	0.137
24	0.207	0.120
25	0.173	0.100
26	0.147	0.085

Table 16 (cont'd)

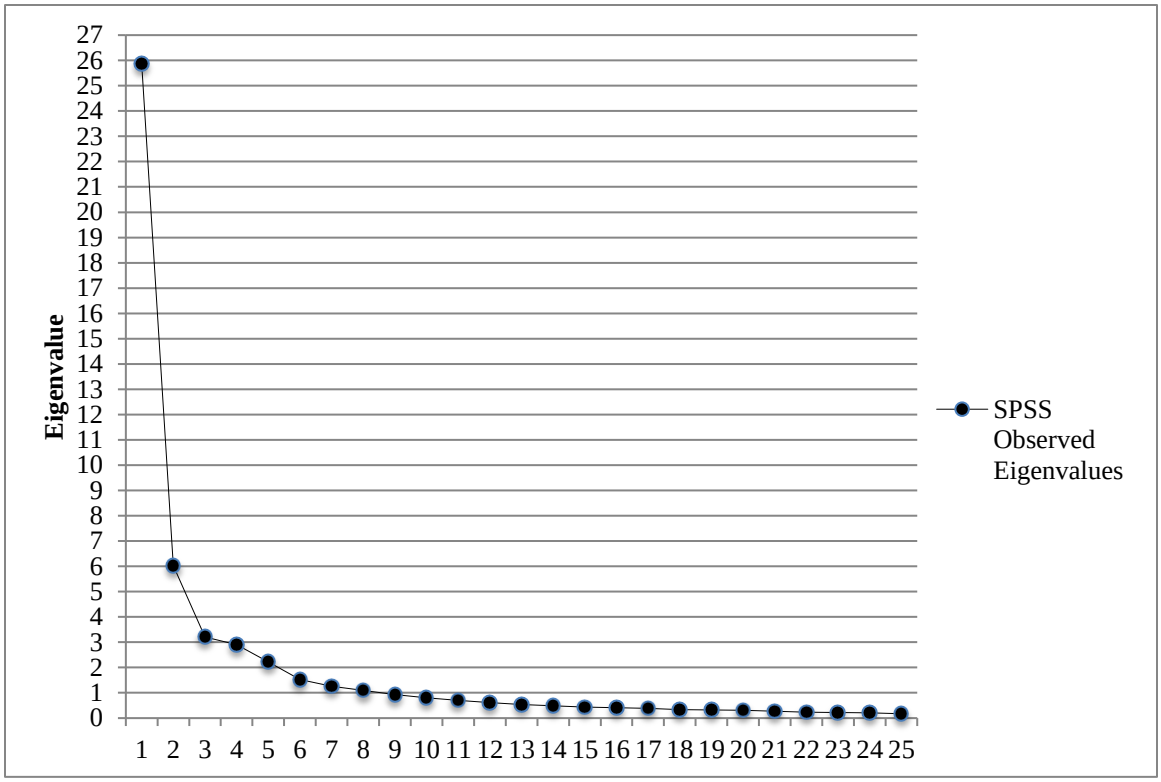
27	0.129	0.069
28	0.121	0.052
29	0.098	0.024
30	0.089	0.017
31	0.071	0.011
32	0.043	-0.018
33	0.042	-0.022
34	0.030	-0.025
35	0.021	-0.037
36	0.009	-0.044
37	-0.002	-0.059
38	-0.014	-0.060
39	-0.020	-0.068
40	-0.028	-0.070
41	-0.032	-0.096
42	-0.043	-0.111
43	-0.051	-0.111
44	-0.063	-0.114
45	-0.067	-0.130
46	-0.075	-0.133
47	-0.079	-0.142
48	-0.091	-0.150
49	-0.095	-0.162
50	-0.095	-0.166
51	-0.104	-0.175
52	-0.120	-0.190
53	-0.129	-0.201
54	-0.129	-0.205
55	-0.144	-0.230
56	-0.159	-0.231
57	-0.208	-0.241
58	-0.212	-0.251

[a] Generated through the SPSS R programming language plugin (Basto & Pereira, 2012; R Core Team, 2013)

The scree test using eigenvalues generated from the SPSS R plugin can be found in Figure 1. The scree test shows a downward curving line with circle-points indicating eigenvalues. The first 25 out of 58 eigenvalues were provided in the figure. The scree test is interpreted by visually inspecting the slope of the line to determine when it becomes level. It

appears that there is a leveling of the slope of the line after the third and fifth eigenvalues. This suggests that a three- and five-factor solution should be considered for retention. The scree plot using eigenvalues from SAS resulted in a similar outcome.

Figure 1. Scree plot with eigenvalues generated from the SPSS R programming language plugin.



A parallel analysis was performed using SPSS with the R programming language plugin. Eigenvalues were generated based on 100 randomly-generated samples resulting from the random arrangement of the 300 cases from the data matrix. Observed eigenvalues were then compared to randomly-generated eigenvalues. Parallel analysis criteria involve retaining observed factors with eigenvalues above the 95th percentile of the randomly generated eigenvalues (Glorfield, 1995). Table 17 shows both the observed and randomly generated eigenvalues above the 95th percentile. Figure 2 provides a graphic depiction of the observed and randomly generated eigenvalues for twenty potential factors and Figure 3 provides a close-up

version of the section of the plot where the observed and randomly generated eigenvalues cross. The first six factors show observed eigenvalues above the random eigenvalues at the 95th percentile with the seventh factor eigenvalue falling below the random eigenvalue at the 95th percentile. Therefore, based upon selection criteria for parallel analysis, six factors should be retained.

Table 17. *Parallel Analysis with Observed and Random Eigenvalues at the 95th Percentile*

Potential Factor	Observed Eigenvalue SPSS[a]	Random Eigenvalue 95th Percentile SPSS
1	25.862	2.007
2	6.032	1.802
3	3.205	1.755
4	2.899	1.624
5	2.221	1.536
6	1.527	1.480
7	1.254	1.397
8	1.094	1.317
9	0.930	1.278
10	0.797	1.256
11	0.704	1.213
12	0.619	1.119
13	0.543	1.081
14	0.481	1.044
15	0.436	0.974
16	0.417	0.928
17	0.385	0.894
18	0.337	0.871
19	0.327	0.799
20	0.309	0.750
21	0.272	0.740
22	0.235	0.698
23	0.220	0.658
24	0.207	0.610
25	0.173	0.594
26	0.147	0.533
27	0.129	0.510
28	0.121	0.477
29	0.098	0.457
30	0.089	0.404

Table 17 (cont'd)

31	0.071	0.372
32	0.043	0.359
33	0.042	0.318
34	0.030	0.288
35	0.021	0.279
36	0.009	0.240
37	-0.002	0.170
38	-0.014	0.159
39	-0.020	0.125
40	-0.028	0.118
41	-0.032	0.090
42	-0.043	0.062
43	-0.051	0.044
44	-0.063	-0.025
45	-0.067	-0.050
46	-0.075	-0.071
47	-0.079	-0.079
48	-0.091	-0.088
49	-0.095	-0.113
50	-0.095	-0.137
51	-0.104	-0.173
52	-0.120	-0.221
53	-0.129	-0.235
54	-0.129	-0.261
55	-0.144	-0.268
56	-0.159	-0.294
57	-0.208	-0.322
58	-0.212	-0.361

[a] Generated through the SPSS R programming language plugin (Basto & Pereira, 2012; R Core Team, 2013)

Figure 2. *Graphic* depiction of parallel analysis with observed and random eigenvalues at the 95th percentile generated from the SPSS R programming language plugin.

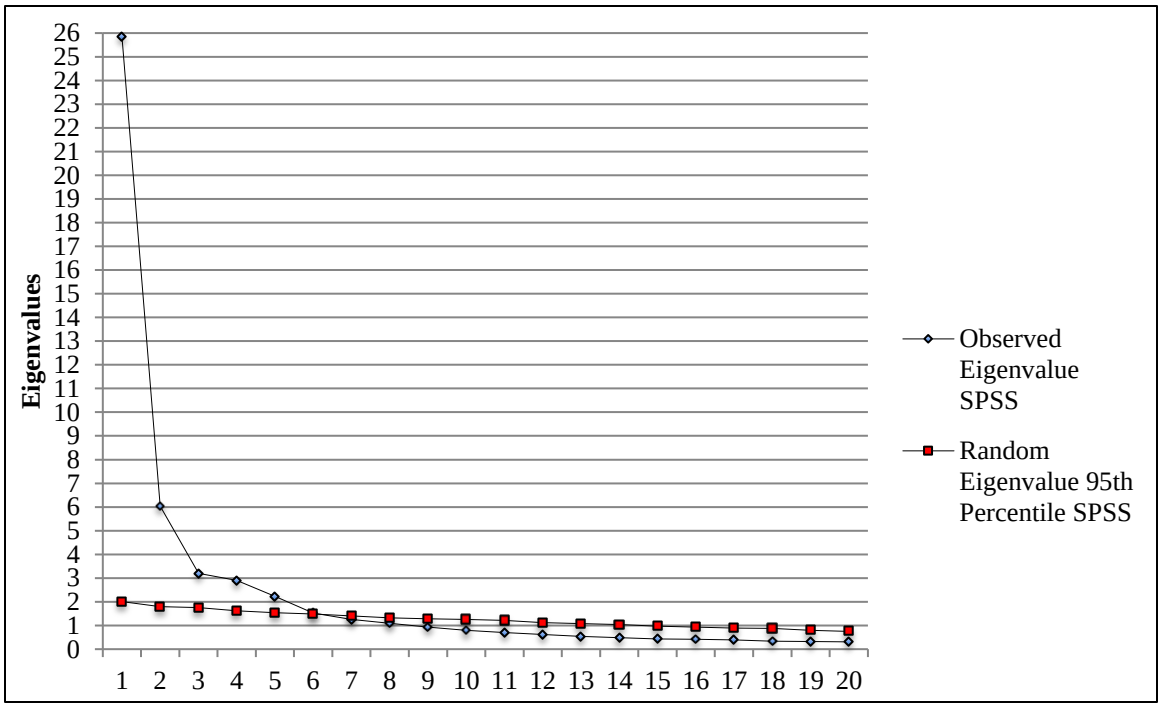
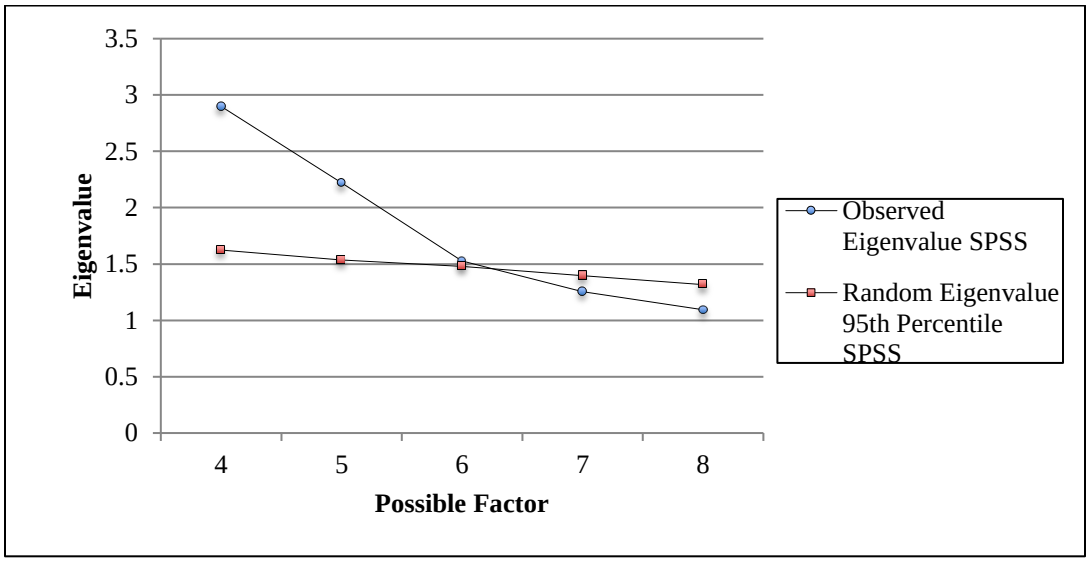


Figure 3. Close-up graphic depiction of parallel analysis with observed and random eigenvalues at the 95th percentile generated from the SPSS R programming language plugin.



The MAP test (Velicer, 1976) was performed using SPSS with the R programming language plugin. With the MAP test, common variance is partialed out for each successive

factor. According to criteria for the MAP test, the number of factors to retain is determined when common variance of the factors reaches its minimum point and only unique variance is leftover (Osborne & Banjanovic, 2016). Table 18 lists results from the MAP test with both squared average partial correlations and fourth average partial correlations. Of note, fourth average partial correlations represent a revision to the original MAP test analysis where partial correlations were raised to the fourth rather than second power in order to improve accuracy (Velicer, Eaton, & Fava, 2000). Figure 4 shows a graphic depiction of results from Velicer's MAP Test. Figure 5 shows a graphic close-up depiction of results from Velicer's MAP Test in order to more clearly see the lowest point of common variance. Results show that the ninth factor represents the lowest squared average and fourth average partial correlations (.024747 and .001924). Therefore, based upon selection criteria for Velicer's MAP test, nine factors should be retained.

Table 18. *Velicer's MAP Test Depicting Squared Average and Fourth Average Partial Correlations*

Factors	Squared Average Partial Correlations	Fourth Average Partial Correlations
0	0.210038	0.067315
1	0.057368	0.011496
2	0.036130	0.006625
3	0.036092	0.005847
4	0.031552	0.004565
5	0.027842	0.003197
6	0.027794	0.002660
7	0.026944	0.002417
8	0.025758	0.002143
9	0.024747	0.001924
10	0.025014	0.001956
11	0.025175	0.001934
12	0.025504	0.002053
13	0.025647	0.001985
14	0.026488	0.002111
15	0.027207	0.002188

Table 18 (cont'd)

16	0.028621	0.002426
17	0.029897	0.002695
18	0.030843	0.002831
19	0.031370	0.002975
20	0.032785	0.003260
21	0.034085	0.003599
22	0.036093	0.003872
23	0.037705	0.004396
24	0.039461	0.004687
25	0.041632	0.005258
26	0.043012	0.005568
27	0.045810	0.006063
28	0.048094	0.006600
29	0.051437	0.007517
30	0.054607	0.008419
31	0.058213	0.009740
32	0.062627	0.010923
33	0.067090	0.012248
34	0.071661	0.014384
35	0.075109	0.015361
36	0.082869	0.017988
37	0.088717	0.020249
38	0.097853	0.023948
39	0.104711	0.026402
40	0.116717	0.032614
41	0.123776	0.036685
42	0.140867	0.045068
43	0.163285	0.058459
44	0.192270	0.077660
45	0.214888	0.096727
46	0.257332	0.131721
47	0.332690	0.199973
48	0.505133	0.377962
49	0.949247	0.917868
50	0.115296	0.033543
51	0.135269	0.044262
52	0.160501	0.059686
53	0.195696	0.082345
54	0.242632	0.118233
55	0.326929	0.193942
56	0.493159	0.367982

Figure 4. Illustration of Velicer's MAP test depicting squared average and fourth average partial correlations.

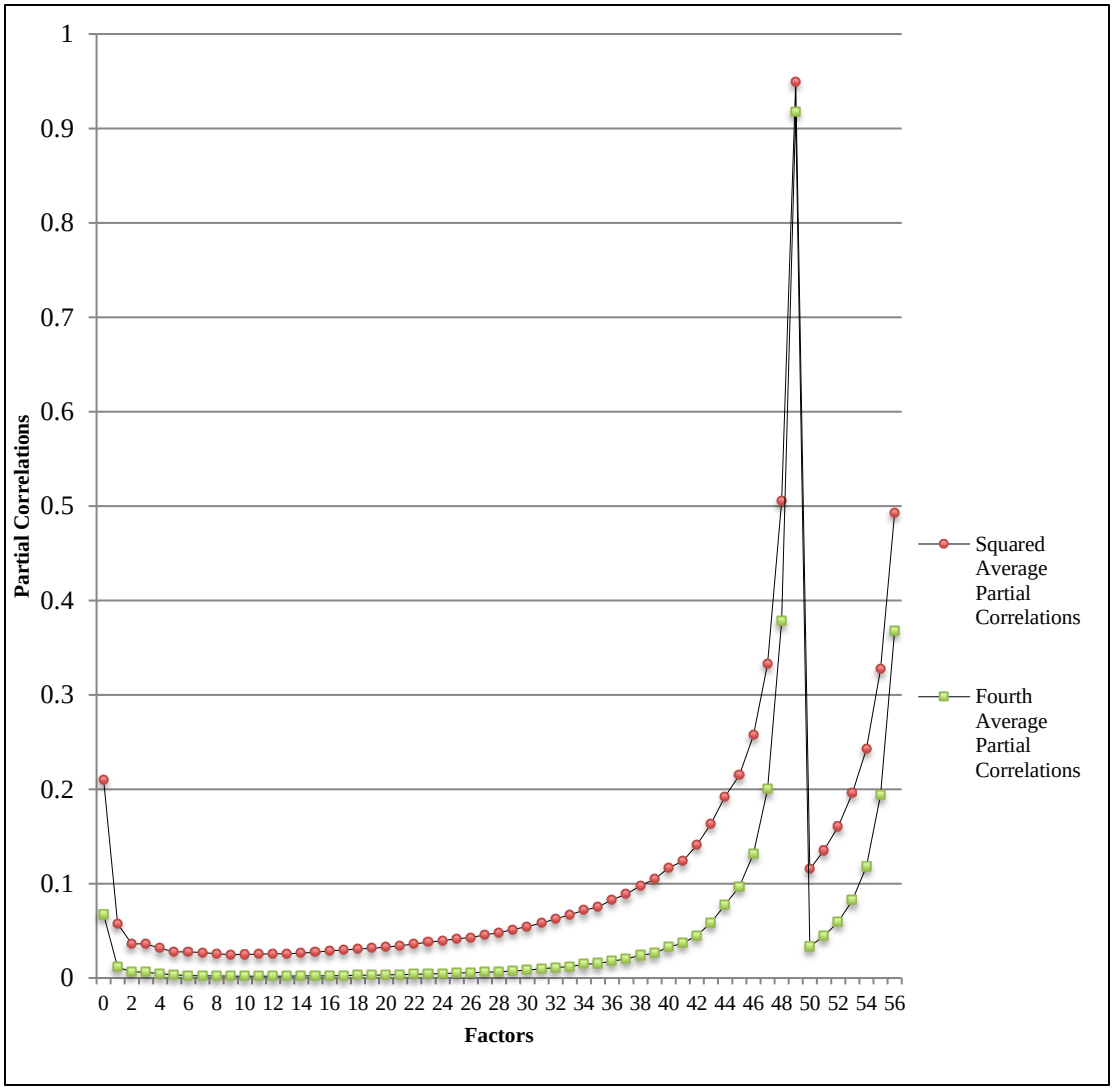
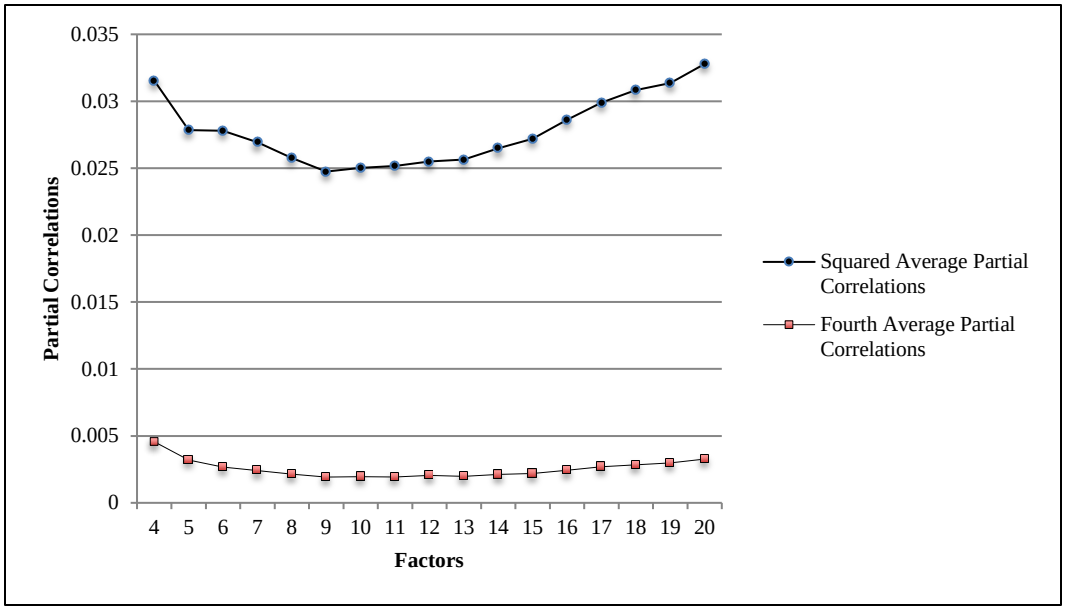


Figure 5. Close-up illustration of Velicer's MAP test depicting squared average and fourth average partial correlations



Summary of initial extraction results. Table 19 summarizes results of the four different factor retention tests. Differing results were found across the four methods. The most weight was provided to the parallel analysis and MAP test given their reputations for greater accuracy (Osborne & Banjanovic, 2016). However, a conservative approach was taken in order to ensure that a thorough examination of all potential solutions would occur. Previous factor analyses of the ABC-C with an ASD sample resulted in 4-, 5-, and 7-factor solutions, with Kaat et al. (2013) also examining a 6-factor solution and Mirwis (2011) examining 7- and 8-factor solutions. Additionally, solutions plus or minus two factors at the highest and lowest range were considered based upon the differing levels of agreement of the factor retention tests. Thus, it was determined to examine the 11-factor solution as well (i.e., plus two above the 9 factor solution suggested by the MAP test). Based upon results from the factor retention tests and previously analyzed factor solutions in the existing literature, 3-, 4-, 5-, 6-, 7-, 8-, 9-, and 10-, and 11-factor solutions were examined for possible retention.

Table 19. *Summary of Factor Retention Test Results*

Method	Suggested Number of Factors to Retain
Guttman-Kaiser Criterion	8
Scree Test	3, 5
Parallel Analysis	6
MAP Test	9

The hypothesis from Research Question 1 stated that between four and seven interpretable factors would be available for retention. Results from the various factor retention tests showed between three and eleven factors possible for retention. Therefore, the hypothesis from Research Question 1 was not supported. Instead the range of factor solutions hypothesized for retention from Research Question 1 was broader than expected.

Research question 2. *How many factors should be retained in order to derive the most interpretable factor solution? Hypotheses 2a, 2b, 2c: there will be at least four factors likely to be retained, an Inappropriate Speech factor will appear, and a Self-Injurious Behavior factor will also appear.* This was determined by examining the pattern and structure matrices resulting from the direct oblimin rotation (Jennrich & Sampson, 1966) for interpretability of factors across the range of possible factor solutions suggested by the previously performed factor retention tests (Guttman-Kaiser Criterion, scree test, parallel analysis, MAP test).

Rotation. A factor rotation was performed in order to more effectively interpret factor loadings. An oblique rotation was used (direct oblimin) given that the factors were expected to be correlated (e.g., Kaat et al., 2013; Mirwis, 2011) and because oblique rotations have been shown to be appropriate even when factors are uncorrelated (Fabrigar & Wegener, 2012). Factor rotation enabled interpretation of the structure and pattern matrices for the 3-, 4-, 5-, 6-, 7-, 8-, 9,

10-, and 11-factor solutions. Factor rotation showed that factors were oblique in all interpretable factor solutions and not orthogonal.

Pattern and structure matrices were generated after an oblique rotation was performed. Pattern matrices contain factor loadings and consist of row statistics of standardized regression coefficients which represent correlations between items and factors. Structure matrices provide the correlations between all pairs of factors in the dataset. Given the distinct nature of the factor loadings in the pattern matrices, the structure matrices were not analyzed for interpretability.

Interpretation. Following extraction and rotation of factors, each of the possible factor solutions were analyzed and named to determine the most interpretable factor solution. Two qualified researchers independently analyzed all factor solutions. Two factor solutions were determined to be the most interpretable of the nine solutions analyzed. Two additional qualified researchers then independently interpreted these two solutions and a consensus final solution was reached among the four researchers.

The three-factor solution was considered given its appearance in the scree test. It represents the most parsimonious possible factor solution of those that were analyzed. Concepts such as tantrums, self-injury, hyperactivity, and impulsivity loaded highly on the first factor. Withdrawal, lethargy, and some elements of stereotypic behavior loaded onto the second factor. Inappropriate speech items along with a stereotypic behavior item loaded on the third factor. Overall, factor constructs in all three of the factors were difficult to interpret; therefore this solution was not chosen.

The four-factor solution was considered given its presence in Brinkley et al. (2007) as well as it being in the range of possible solutions (plus or minus two) based upon the parallel analysis. Factors included an Externalizing Behavior factor (consisting of concepts such as

tantrums, irritability, self-injury, agitation, and hyperactivity), a Lethargy/Withdrawal factor, a Stereotypic Behavior/Hyperactivity factor, and an Inappropriate Speech factor. The Externalizing Behavior factor as well as the Stereotypic Behavior/Hyperactivity factors seemed to combine multiple constructs making them challenging to cleanly define. The Inappropriate Speech factor and the Lethargy/Withdrawal factor were much more interpretable. However, because two of the factors were too conceptually difficult to adequately interpret, the four-factor solution was not chosen.

The five-factor solution was considered given its appearance in the scree test, the fact that it consisted of the same number of factors as the current author version of the ABC-C (Aman & Singh, 2017) and one of the Brinkley et al. (2007) solutions, and because it was in the range of possible solutions based upon the parallel analysis. A fair number of crossloadings occurred across all factors though most crossloadings were < .40. Three distinct factors emerged: a Stereotypic Behavior factor, an Inappropriate Speech factor, and a Hyperactivity factor. The two other factors that appeared were more conceptually dense. A Self-injury/Irritability factor emerged with the three self-injury items loading the highest (.94, .92, .90) and the next highest loadings including tantrums and aggressive behavior items (.83, .74, .70). A Social Withdrawal/Noncompliance factor also arose as the largest factor with 22 items. Overall, the two factors with multiple constructs seemed to likely be more interpretable if they were further narrowed. Additionally, the five-factor solution was not specifically suggested by the parallel analysis or the MAP test. Therefore, the five-factor solution was not chosen.

The seven-factor solution was considered given that Mirwis (2011) settled on a seven-factor solution in his study and it was in the range of possible solutions based on the parallel analysis, and the MAP test. Three factors emerged that were relatively distinct: a Lethargy

factor, an Inappropriate Speech factor, and a Stereotypic Behavior factor. Two other factors appeared (a Hyperactivity factor and a Withdrawal/Noncompliance factor) that each shared one exact crossing loading with the Irritability/Agitation factor. A Self-Injury/Aggressiveness factor also emerged, which shared two equal loadings with the Irritability/Agitation factor. Overall, given the fact that the various crossloadings raised questions regarding the strength of the Irritability/Agitation factor, and the fact that this solution was not identified in the parallel analysis, or the MAP test, the seven-factor solution was therefore not chosen.

The eight-factor solution was considered as a result of the Guttman-Kaiser Criterion, which specified eight-factors, and it was in the range of possible solutions based on the parallel analysis and the MAP test. Immediately apparent was the eighth factor, which included only two items with loadings respectively at .58 and .56. These two items seem to signify a physical withdrawal construct. However, with only two items and each with moderate loadings, it was not enough to maintain a complete factor. The other factors that emerged were readily interpretable. They included an Irritability factor, a Hyperactivity factor, a Withdrawal/Noncompliance factor, a Stereotypic Behavior factor, a Lethargy factor, a Self-Injury/Aggressiveness factor, and an Inappropriate Speech factor. Overall, given the lack of a complete eighth factor, this solution was not chosen.

The ten-factor solution was considered because it was in the range of possible solutions of the MAP test. The tenth factor that appeared maintained four items with moderate to low loadings (.50, .46, .38, .32). These items were conceptually difficult to conceptualize into a meaningful construct. As a result this factor solution was not chosen.

The eleven-factor solution was also considered as a result of it being in the range of possible solutions of the MAP test. The tenth factor emerged with only two loadings. The

eleventh factor emerged with four very weak loadings (.42, .38, .37, and .35) making it challenging to appropriately interpret. Overall, given these two problematic factors, this factor solution was not selected.

Both the six-factor and nine-factor solutions were deemed to be the two best solutions out of all solutions that were analyzed. In order to choose between them, a consensus opinion was sought across four qualified raters who rated the two solutions independently. Three of the four raters agreed upon the same final solution.

The six-factor solution was considered as a result of the parallel analysis. It emerged with three relatively distinct factors: Hyperactivity, Inappropriate speech, and Stereotypic Behavior. It also had two other distinct factors (a Social Withdrawal/Noncompliance factor and a Lethargy factor) that shared a weaker crossloading item (.38). Finally a Self-Injury/Tantrums/Irritability factor emerged with the three highest loadings (.95, .95, and .91) representing all self-injurious behavior items and the next highest loadings (.77, .69, .68) regarding tantrums and aggressive behavior.

The nine-factor solution was considered as a result of the MAP test. Three similar factors as the six-factor solution emerged: a Hyperactivity factor, an Inappropriate Speech factor, and a Stereotypic Behavior factor. The Social Withdrawal/Noncompliance factor in the six-factor solution was split into two distinct factors (a Social Withdrawal factor and a Noncompliance factor). The Self-Injury/Tantrums/Irritability factor in the six-factor solution was split into two factors: a Self-Injury/Aggressiveness factor, and an Irritability/Tantrums factor. Two other factors also emerged: a Lethargy factor and an Oppositionality factor.

The question emerged whether the six-factor, Self-Injury/Tantrums/Irritability factor was too conceptually crowded and whether a more expanded factor structure, such as the nine-factor

structure, would be more theoretically and practically useful. Three of the four qualified researchers agreed that the nine-factor solution maintained factors that were conceptually clear with item loadings that were relatively high. It was determined that expanding to nine factors did not result in factor constructs that were too narrow. As such, the six-factor solution was not selected and the nine-factor solution was chosen.

Table 20 represents the nine-factor solution pattern matrix. See Appendix H for the nine-factor solution structure matrix. As mentioned previously the nine-factors were interpreted as follows: I-Hyperactivity, II-Stereotypic Behavior, III-Self-Injury/Aggressiveness, IV-Social Withdrawal, V-Inappropriate Speech, VI-Lethargy, VII-Irritability/Tantrums, VIII-Noncompliance, IX-Oppositionality.

Table 20. *Nine-Factor Solution Pattern Matrix*

		Assigned Factor Number								
Item #	Stem	1	2	3	4	5	6	7	8	9
15	Restless, unable to sit still	**0.86**	0.07	0.01	0.02	0.08	0.10	0.05	-0.05	-0.04
54	Tends to be excessively active	**0.82**	0.06	0.12	0.11	0.06	-0.15	0.03	-0.05	-0.03
1	Excessively active at home, school, work, or elsewhere	**0.81**	0.06	-0.03	-0.03	0.04	-0.12	0.05	0.01	0.05
39	Will not sit still for any length of time	**0.81**	0.05	0.07	-0.11	-0.10	0.07	-0.05	0.10	-0.01
38	Does not stay in seat (e.g., during lesson or training periods, meals, etc.)	**0.69**	0.05	-0.03	0.09	-0.14	-0.11	0.16	0.13	0.11
48	Constantly runs or jumps around the room	**0.64**	0.18	0.19	0.08	-0.02	-0.08	0.07	0.04	-0.04
7	Boisterous (inappropriately noisy and rough)	**0.36**	0.24	0.19	-0.17	0.27	0.03	0.06	0.04	0.25
13	Impulsive (acts without thinking)	**0.34**	0.14	0.10	0.01	0.09	-0.10	0.16	0.24	0.25

Table 20 (cont'd)

35	Repetitive hand, body, or head movements	-0.04	**0.88**	0.06	0.10	0.05	-0.05	-0.02	0.04	0.00
6	Meaningless, recurring body movements	0.00	**0.81**	0.12	0.12	0.13	-0.08	0.00	-0.03	-0.04
45	Waves or shakes the extremities repeatedly	0.19	**0.76**	-0.04	0.13	-0.07	-0.03	0.05	0.00	-0.15
11	Stereotyped behavior; abnormal, repetitive movements	-0.02	**0.76**	0.11	0.15	0.06	-0.11	0.02	0.11	0.02
27	Moves or rolls head back and forth repetitively	-0.01	**0.75**	0.02	-0.10	0.02	0.24	-0.05	-0.07	0.20
49	Rocks body back and forth repeatedly	0.19	**0.73**	-0.02	-0.08	-0.03	0.13	-0.03	0.00	-0.05
17	Odd, bizarre in behavior	0.12	**0.43**	0.09	0.21	0.18	-0.02	0.05	0.17	0.08
52	Does physical violence to self	-0.01	0.06	**0.96**	0.01	-0.06	-0.03	-0.02	0.06	-0.02
2	Injures self on purpose	0.02	0.08	**0.93**	-0.04	-0.04	0.04	0.03	-0.05	0.00
50	Deliberately hurts himself/herself	0.07	0.07	**0.93**	-0.02	0.01	0.05	0.00	-0.03	-0.07
47	Stamps feet or bangs objects or slams doors	0.20	-0.04	**0.49**	-0.04	0.22	0.04	0.08	0.06	0.07
4	Aggressive to other children or adults (verbally or physically)	0.02	0.06	**0.45**	-0.06	0.06	-0.11	0.14	0.03	0.42
30	Isolates himself/herself from other children or adults	-0.01	0.18	-0.06	**0.85**	-0.04	0.03	0.13	0.04	0.01
5	Seeks isolation from others	-0.04	0.11	-0.03	**0.83**	0.08	-0.03	0.11	0.07	-0.01
42	Prefers to be alone	-0.03	0.13	-0.04	**0.78**	0.05	0.08	-0.03	0.12	0.09
16	Withdrawn; prefers solitary activities	0.05	0.13	0.05	**0.70**	0.13	0.11	0.07	0.10	-0.13
58	Shows few social reactions to others	0.12	-0.03	0.18	**0.45**	-0.01	0.14	-0.12	0.42	-0.08

Table 20 (cont'd)

55	Responds negatively to affection	0.25	-0.08	0.24	**0.41**	0.07	0.24	-0.32	-0.08	0.34
22	Repetitive speech	-0.07	0.06	0.05	0.03	**0.91**	-0.01	-0.08	0.01	0.02
46	Repeats a word or phrase over and over	-0.12	0.01	0.02	0.02	**0.85**	0.05	0.07	0.08	-0.01
9	Talks excessively	0.11	-0.03	-0.19	-0.09	**0.84**	0.04	0.07	-0.04	0.00
33	Talks to self loudly	-0.03	0.08	0.08	0.15	**0.82**	-0.10	-0.03	-0.08	-0.03
53	Inactive, never moves spontaneously	-0.05	0.05	0.04	-0.04	0.01	**0.80**	0.06	0.25	-0.06
3	Listless, sluggish, inactive	-0.12	0.09	0.14	0.09	-0.04	**0.75**	0.19	-0.11	-0.09
23	Does nothing but sit and watch others	0.01	0.06	-0.12	0.14	0.07	**0.70**	-0.08	0.17	-0.08
32	Sits or stands in one position for a long time	-0.04	0.11	-0.08	0.07	-0.03	**0.58**	0.03	0.10	0.22
20	Fixed facial expression; lacks emotional responsiveness	0.12	0.04	0.12	0.14	0.15	**0.47**	0.01	0.16	0.03
25	Depressed mood	-0.10	0.05	0.04	0.18	-0.05	**0.46**	0.23	-0.01	0.32
12	Preoccupied; stares into space	-0.02	0.28	0.08	0.14	0.09	**0.36**	0.03	0.35	-0.17
34	Cries over minor annoyances and hurts	0.07	0.08	-0.02	0.10	0.17	0.18	**0.66**	-0.04	-0.04
14	Irritable and whiny	0.21	0.01	0.01	0.05	-0.06	0.24	**0.64**	-0.08	0.11
41	Cries and screams inappropriately	0.18	-0.03	0.22	0.06	0.19	0.02	**0.62**	0.13	-0.08
10	Temper tantrums / outbursts	0.01	0.01	0.42	0.08	0.03	-0.08	**0.53**	-0.04	0.24
8	Screams inappropriately	0.14	-0.03	0.18	-0.06	0.26	0.04	**0.50**	0.15	0.06
57	Has temper outbursts or tantrums when he/she does not get own way	0.03	-0.04	0.37	0.17	0.03	-0.11	**0.50**	0.05	0.24
19	Yells at inappropriate times	0.19	-0.08	0.24	-0.04	0.33	0.05	**0.44**	0.18	0.01
29	Demands must be met immediately	0.10	0.10	0.13	0.16	-0.06	-0.14	**0.41**	0.15	0.33

Table 20 (cont'd)

36	Mood changes quickly	0.09	0.20	0.31	0.00	-0.06	0.09	**0.34**	0.10	0.18
51	Pays no attention when spoken to	0.06	0.07	0.05	0.14	0.06	0.15	-0.05	**0.67**	0.09
28	Does not pay attention to instructions	0.14	0.16	-0.06	0.19	0.14	0.09	0.05	**0.50**	0.10
43	Does not try to communicate by words or gestures	0.14	0.03	0.16	0.20	-0.21	0.29	0.00	**0.46**	-0.07
37	Unresponsive to structured activities (does not react)	0.02	0.13	0.09	0.07	-0.13	0.40	-0.02	**0.46**	0.14
56	Deliberately ignores directions	0.07	0.03	-0.03	0.24	0.08	-0.10	0.13	**0.44**	0.34
44	Easily distractible	0.29	0.14	-0.15	0.06	0.18	0.12	0.20	**0.40**	-0.07
40	Is difficult to reach, contact, or get through to	0.13	0.08	0.04	0.37	0.02	0.19	0.04	**0.39**	0.04
21	Disturbs others	0.20	0.15	0.08	-0.10	0.30	-0.08	0.09	0.18	**0.51**
24	Uncooperative	0.02	0.01	0.10	0.14	0.02	0.12	0.25	0.17	**0.51**
18	Disobedient; difficult to control	0.18	0.03	0.21	0.05	0.03	-0.05	0.29	0.11	**0.45**
31	Disrupts group activities	0.19	0.14	0.07	-0.05	0.15	-0.11	0.25	0.26	**0.41**
26	Resists any form of physical contact	0.25	-0.12	-0.05	0.37	0.05	0.37	-0.16	-0.13	**0.39**

Note: Loadings formatted in bold denote assigned factor loading and underlined loadings denote factor loading > 0.30.

Factor I: Hyperactivity. Factor I, Hyperactivity, was composed of the following items: 1, 7, 13, 15, 38, 39, 48, and 54. The highest loading items (15, 54, 1, and 39) best described the factor construct including being restless and unable to sit still (factor loading = .86), being excessively active (.82), being excessively active in multiple environments (.81), and not being able to sit still for any length of time (.81). The two lowest loading items (7 and 13) included being boisterous (.36) and impulsive (.34). No items $\geq$ .30 crossloaded on this factor.

Factor II: Stereotypic Behavior. Factor II, Stereotypic Behavior, comprised the following items: 6, 11, 17, 27, 35, 45, and 49. The first six loadings are all $\geq$ .73, which, according to criteria outlined by Comrey and Lee (as cited in Pett et al., 2003) are considered excellent loadings. These items helped to best characterize this factor as one consisting of repetitive movements (.88), recurring body movements (.81), stereotyped behavior (.76), and repeated body rocking (.73). The lowest loading item was item 17: odd, bizarre in behavior (.43). No items $\geq$ .30 crossloaded on this factor.

Factor III: Self-Injury/Aggressiveness. Factor III, Self-Injury/Aggressiveness, was composed of the following items: 2, 4, 47, 50, and 52. The first three loadings, all $\geq$ .93, are the highest loading items in the entire matrix and best describe this factor as doing physical violence to oneself (.96), injuring oneself on purpose (.93), and deliberately hurting oneself (.93). The last two loadings (items 2 and 4) are fair in strength and do not directly support a self-injurious behavior construct. These two items best represent an aggressiveness construct including stomping feet, banging objects and slamming doors (.49), and being verbally or physically aggressive to others (.45). Item 4 (.45) also maintains a crossloading (.42) with factor IX.

Factor IV: Social Withdrawal. Factor IV, Social Withdrawal, comprised the following items: 5, 16, 30, 42, 55, and 58. The first four loadings, all $\geq$ .70, are the highest loading items in the factor and characterize the factor as isolating oneself from others (.85), seeking isolation from others (.83), preferring to be alone (.78) and preferring solitary activities (.70). The two remaining items (58 and 55) are weaker loadings (.45 and .41) and appear somewhat divergent with regard to the social withdrawal construct. They include showing few social reactions to others (.45) and responding negatively to affection (.41). Item 58 (.45) maintains a crossloading on factor VIII (.42), and item 55 (.41) maintains a crossloading on factor IX (.34).

Factor V: Inappropriate Speech. Factor V, Inappropriate Speech was composed of the four following items: 9, 22, 33, and 46. All loadings are ≥ .82 and describe the factor as consisting of different aspects of inappropriate speech such as repetitive speech (.91), repeating a word or phrase over and over (.85), talking excessively (.84), and talking loudly to self (.82). No items ≥ .30 crossloaded on this factor.

Factor VI: Lethargy. Factor VI, Lethargy, was composed of the following items: 3, 12, 20, 23, 25, 32, and 53. The three highest loading items are ≥ .70 and best characterize the factor by never moving spontaneously (.80), sluggish and inactive (.75), and doing nothing but sitting and watching others (.70). Item 32 (.58) maintains a similar description with regard to maintaining a single position for a long period of time while item 20 (.47) highlights a lack of emotional responsiveness. Item 25 (.46) describes a depressed mood, while item 12 (.36) illustrates one being preoccupied and staring into space. Item 25 maintains a crossloading with Factor IX (.32) and item 12 maintains a crossloading with factor VIII (.35).

Factor VII: Irritability/Tantrums. Factor VII, Irritability/Tantrums, was composed of the following items: 8, 10, 14, 19, 29, 34, 36, 41, and 57. The three highest loading items (34, 14, and 41) describe the irritability aspect of the factor by crying over minor annoyances (.66), irritable and whiny (.64), and crying and screaming inappropriately (.62). The next four highest loading items (10, 8, 57, and 19) characterize the tantrum construct of the factor by temper tantrums and outbursts (.53), screaming inappropriately (.50), tantrums when one does not get her way (.50), and yelling at inappropriate times (.44). The two lowest loading items (item 29 and 36) involve demands needing to be met immediately (.41) and quickly changing mood (.34). Item 10 (.53) maintains a crossloading with Factor III (.42), item 57 (.50) maintains a

crossloading with Factor III (.37), item 29 (.41) maintains a crossloading with Factor IX (.33), and item 36 (.34) maintains a crossloading with Factor III (.31).

Factor VIII: Noncompliance. Factor VIII, Noncompliance, comprised the following items: 28, 37, 40, 43, 44, 51, and 56. The highest three loading items (51, 28, 43, 37, and 56) characterize the factor best by not paying attention when spoken to (.67), not paying attention to instructions (.50), not communicating by words or gestures (.46), unresponsive to structured activities (.46), and deliberately ignoring directions (.44). The lowest loading items (44 and 40) do not directly characterize the factor, consisting of being easily distractible (.40) and being difficult to reach, contact, or get through to (.39). Item 37 (.46) maintains a crossloading with Factor VI (.40), item 56 (.44) maintains a crossloading with factor IX (.34), and item 40 (.39) maintains a cross loading with Factor IV (.37).

Factor IX: Oppositionality. Factor IX, Oppositionality, consists of the following items: 18, 21, 24, 26, and 31. The four highest loading items (21, 24, 18, and 31) describe the factor by disturbing others (.51) and being uncooperative (.51), being disobedient and difficult to control (.45), and disrupting group activities (.41). The final item (26) is characterized by resisting any form of physical contact (.39). Item 21 (.51) maintains a crossloading with Factor V, and item 26 (.39) maintains a crossloading with Factor IV (.37) and Factor VI (.37).

Research question 2 summary. Once the nine-factor solution was fully interpreted, Hypotheses 2a, 2b, and 2c could be assessed. Hypothesis 2a was supported (at least four factors would be retained) because nine factors were retained. Hypothesis 2b was also supported (an Inappropriate Speech factor would appear) because an Inappropriate Speech Factor appeared as Factor V. Hypothesis 2c was not fully supported (a Self-Injurious Behavior factor would appear). Although the highest loading items in Factor III consisted of the self-injurious behavior

items, the remaining items were deemed as a related but separate construct, thus resulting in the factor being labeled Self-Injurious Behavior/Aggressiveness.

Research question 3. *Does the most interpretable factor structure yield substantive correlations amongst the factors? Hypothesis: there will be substantive correlations (i.e., > .30; Beavers et al., 2013) amongst at least some factors.* This was determined by analyzing the relations in the inter-factor correlation matrix of the chosen factor solution after the oblique rotation (i.e., direct oblimin). Correlations between the factors of the nine-factor solution were evaluated. Table 21 contains the inter-factor correlations.

Table 21. *EFA Inter-Factor Correlation Matrix Nine-Factor Solution*

		Factor								
		I	II	III	IV	V	VI	VII	VIII	IX
Factor	I: Hyperactivity	1.000								
	II: Stereotypic Behavior	**0.43**	**1.**000							
	III: Self-Injury/Aggressiveness	**0.41**	**0.36**	1.000						
	IV: Social Withdrawal	0.26	**0.39**	0.21	1.000					
	V: Inappropriate Speech	0.24	0.28	0.18	0.19	1.000				
	VI: Lethargy	0.09	0.28	0.09	**0.45**	0.02	1.000			
	VII: Irritability/Tantrums	**0.35**	0.25	**0.41**	0.15	0.29	0.10	1.000		
	VIII: Noncompliance	**0.38**	**0.38**	0.25	**0.43**	0.19	**0.31**	0.29	1.000	
	IX: Oppositionality	**0.35**	0.12	**0.34**	0.27	0.19	0.16	**0.30**	0.20	1.000

Non-identity values that are ≥ 0.30 are presented in bold print.

Factor I, Hyperactivity, had a moderate correlation with Factor II, Stereotypic Behavior (.43), Factor III, Self-Injury/Aggressiveness (.41), Factor VII, Irritability/Tantrums (.35), Factor

VIII, Noncompliance (.38), and Factor IX, Oppositionality (.35). Factor II, Stereotypic Behavior, had a moderate correlation with Factor III, Self-Injury/Aggressiveness (.36), Factor IV, Social Withdrawal (.39), and Factor VIII, Noncompliance (.38). Factor III, Self-Injury/Aggressiveness, had a moderate correlation with Factor VII, Irritability/Tantrums (.41), and Factor IX, Oppositionality (.34). Factor IV, Social Withdrawal, had a moderate correlation with Factor VI, Lethargy, and with Factor VIII, Noncompliance (.43). Factor V, Inappropriate Speech, did not have any moderate correlations with any factors, but maintained a low correlation with Factor I, Hyperactivity (.24), Factor II, Stereotypic Behavior (.28), and Factor VII, Irritability/Tantrums (.29). Factor VI, Lethargy, had a moderate correlation with Factor VIII, Noncompliance (.31). Factor VII, Irritability/Tantrums, had a moderate correlation with Factor IX, Oppositionality (.30).

Additionally, internal consistency reliability estimates were calculated using ordinal alpha as well as Cronbach's alpha, in order to maintain a common standard for comparison with previous studies that did not use ordinal alpha. Ordinal alpha estimates were chosen as the primary estimate of internal consistency reliability because of the use of the polychoric correlation matrix. See Table 22 for the nine-factor solution internal consistency reliability estimates.

Table 22. *Ordinal Alpha and Cronbach's Alpha for the Nine-Factor ABC-C Solution*

Factor	Factor Name	Ordinal Alpha Estimate	Cronbach's Alpha Estimate
I	Hyperactivity	.948	.922
II	Stereotypic Behavior	.943	.907
III	Self-Injury/Aggressiveness	.926	.888
IV	Social Withdrawal	.940	.910
V	Inappropriate Speech	.913	.861

Table 22 (cont'd)

VI	Lethargy	.904	.816
VII	Irritability/Tantrums	.951	.931
VIII	Noncompliance	.933	.901
IX	Oppositionality	.889	.856

Ordinal alpha estimates ranged from .889 to .951 with eight of the nine factors $\geq$ .90. Cronbach's alpha estimates ranged from .816 to .931 with five of the nine factors $\geq$ .90. Based upon criteria provided by Murphy and Davidshofer (as cited in Sattler, 2008) estimates from .80 to .89 are considered to be moderately high or good reliability, while estimates from .90 to .99 are considered excellent. Thus, internal consistency reliability estimates for the nine-factor solution were mostly in the excellent range.

Overall, eight of the nine factors maintained substantive correlations between them. Only Factor V, Inappropriate Speech, failed to generate a substantive correlation with the other factors. Therefore, Hypothesis 3 was fully supported because nearly all of the factors maintained substantive correlations between them.

Research question 4. *If a five-factor solution is interpretable, to what extent does the solution correspond to the five-factors hypothesized by the test authors? Hypothesis: the five-factor solution, from among the EFA solutions, will closely match the test-authors' proposed five-factor solution.* This was determined by a) qualitatively comparing the factor construct names of the test authors' five-factor ABC-C solution and this study's derived five-factor solution, b) qualitatively comparing the highest loading items that are instrumental in defining/naming each factor on the test author's solution and this study's derived solution, and c)

calculating a percentage of overlapping items between the factors from the derived five-factor solution and the ABC-C authors' version.

Table 23 compares factor names for the Aman and Singh (2017) five-factor solution and the five-factor solution that was generated (though not ultimately chosen) from the EFA in this study (FFSEFA). Similar factor constructs were derived from both analyses although they did not occur in the same factor order. Chosen factor names for the constructs in the FFSEFA were comparable to the names chosen by Aman and Singh (2017). Inappropriate Speech and Stereotypic Behavior factor names were exactly the same in both solutions. The Irritability factor in Aman and Singh (2017) was named Self-Injury/Irritability in the FFSEFA because the three self-injury items were the highest loading items in the factor. The noncompliance construct was found in both Aman and Singh (2017) and in the FFSEFA, although it paired with the social withdrawal construct in the FFSEFA instead of with the hyperactivity construct as it did in Aman and Singh (2017). The hyperactivity construct constituted a separate factor in the FFSEFA and the social withdrawal construct constituted a separate factor in Aman and Singh (2017). Overall, factor constructs and thus factor names were deemed similar between the two five-factor solutions.

Table 23. *Factor Names From the Aman and Singh (2017) Five-Factor Solution and the Five-Factor Solution From Study One*

Factor	Factor Names Aman and Singh (2017) Five-Factor Solution	Factor Names Five-Factor Solution Study One
I	Irritability	Social Withdrawal/Noncompliance
II	Social Withdrawal	Self-Injury/Irritability
III	Stereotypic Behavior	Hyperactivity
IV	Hyperactivity/Noncompliance	Inappropriate Speech
V	Inappropriate Speech	Stereotypic Behavior

Table 24 compares the highest loading items that were instrumental in naming each factor found in Aman and Singh (2017) and the FFSEFA. Both the Inappropriate Speech and Stereotypic Behavior factors in the Aman and Singh (2017) model and the FFSEFA are nearly identical in terms of their highest loading items. Only one item is reversed in position (Item 11) in the Stereotypic Behavior factor in Aman and Singh (2017) and the FFSEFA. The highest loadings in the Self Injury/Irritability factor in the FFSEFA differs primarily from the highest loadings in the Aman and Singh (2017) model because all three self-injury items represent the highest loading items on the factor in the FFSEFA. The first appearance of a self-injury item occurs in the fifth highest loading in the Irritability factor in the Aman and Singh (2017) model and its actual loading (.68) is lower than the other self-injury item loadings in the FFSEFA. Four of the highest loading items in the Hyperactivity/Noncompliance factor in the Aman and Singh (2017) model are in the Hyperactivity factor in the FFSEFA except they have differing loading positions. Three of the highest loading items in the Social Withdrawal factor in Aman and Singh (2017) were found in the Social Withdrawal/Noncompliance factor in the FFSEFA (23, 42, and 37), although all loading in different orders. The two different items (item 53 and item 30) in the FFSEFA and in Aman and Singh (item16 and item 32) are also high loading items found in each of the different factors, though with different loading levels. Overall, a qualitative comparison of the highest loading items among similar factors in the Aman and Singh (2017) model and the FFSEFA showed a great number of item similarities though differences in the order and strength of the loadings.

Table 24. *Highest Loading Items in the Aman and Singh (2017) Five-Factor Solution and the Five-Factor Solution From Study One*

Factor Names Aman and Singh (2017) Five-Factor Solution	Highest Loading Items Aman and Singh (2017) Five-Factor Solution	Factor Names Five-Factor Solution Study One	Highest Loading Items Five-Factor Solution Study One (loading)
Social Withdrawal	•Item 16: Withdrawn; prefers solitary activities (.64) •Item 37: Unresponsive to structured activities (does not react; 63) •Item 32: Sits or stands in one position for a long time (.63) •Item 42: Prefers to be alone (.63) •Item 23: Does nothing but sit and watch others (.62)	Social Withdrawal /Noncompliance	•Item 23: Does nothing but sit and watch others (.85) •Item 53: Inactive, never moves spontaneously (.84) •Item 42: Prefers to be alone (.82) •Item 30: Isolates himself/herself from other children or adults (.78) •Item 37: Unresponsive to structured activities (does not react) (.75)
Irritability	•Item 10: Temper tantrums/outburst (.81) •Item 57: Throws temper outbursts or tantrums when he/she does not get own way (.78) •Item 29: Demands must be met immediately (.70) •Item 14: Irritable and whiny (.70) •Item 52: Does physical violence to self (.68)	Self-Injury/Irritability	•Item 2: Injures self on purpose (.94) •Item 52: Does physical violence to self (.92) •Item 50: Deliberately hurts himself/herself (.90) •Item 10: Temper Tantrums/outbursts (.83) •Item 57: Has temper outbursts or tantrums when he/she does not get own way (.74)
Hyperactivity /Noncompliance	•Item 39: Will not sit still for any length of time (.71) •Item 48: Constantly runs or jumps around the room (.67) •Item 54: Tends to be excessively active (.67) •Item 38: Does not stay in seat (e.g., during lesson or learning periods, meals, etc.; .63) •Item 1: Excessively active at home, school, work, or elsewhere (.61)	Hyperactivity	•Item 1: Excessively active at home, school, work, or elsewhere (.83) •Item 54: Tends to be excessively active (.80) •Item 38: Does not stay in seat (.79) •Item 39: Will not sit still for any length of time (.79) •Item 15: Restless, unable to sit still (.77)

Table 24 (cont'd)

Inappropriate Speech	•Item 22: Repetitive Speech (.81) •Item 46: Repeats a word or phrase over and over (.77) •Item 9: Talks excessively (.71) •Item 33: Talks to self (.68)	Inappropriate Speech	•Item 22: Repetitive Speech (.89) •Item 46: Repeats a word or phrase over and over (.86) •Item 9: Talks Excessively (.85) •Item 33: Talks to self loudly (.83)
Stereotypic Behavior	•Item 35: Repetitive hand, body, or head movements (.78) •Item 6: Meaningless, recurring body movements (.76) •Item 11: Stereotyped behavior, abnormal, repetitive movements (.71) •Item 45: Waves or shakes the extremities repeatedly (.63) •Item 49: Rocks body back and forth repeatedly (.62)	Stereotypic Behavior	•Item 35: Repetitive hand, body, or head movements (.73) •Item 6: Meaningless, recurring body movements (.70) •Item 45: Waves or shakes the extremities repeatedly (.67) •Item 11: Stereotyped behavior; abnormal, repetitive movements (.63) •Item 49: Rocks body back and forth repeatedly (.62)

Table 25 provides the percentage of overlapping items between the factors from the FFSEFA and the Aman and Singh (2017) model.

Table 25. *Percentage of Overlapping Items from the Five-Factor Solution From Study One Compared to the Aman and Singh (2017) Five-Factor Solution*

Factor Names: Aman and Singh (2017) Five-Factor Solution	Items in Each Factor: Aman and Singh (2017) Five-Factor Solution	Factor Names: Five-Factor Solution Study One	Items in Each Factor: Five-Factor Solution Study One	Overlapping Items Between Aman and Singh (2017) and the Five-Factor Solution Study One (Percentage)
Irritability	2, 4, 8, 10, 14, 19, 25, 29, 34, 36, 41, 47, 50, 52, 57	Self-Injury/Irritability	2, 4, 8, 10, 14, 18, 19, 29, 34, 36, 41, 47, 50, 52, 57	14 out of 15 (93%)
Social Withdrawal	3, 5, 12, 16, 20, 23, 26, 30, 32, 37, 40, 42, 43, 53, 55, 58	Social Withdrawal/ Noncompliance	3, 5, 12, 16, 20, 23, 24, 25, 26, 28, 30, 32, 37, 40, 42, 43, 44, 51, 53, 55, 56, 58	16 out of 16 (100%)

Table 25 (cont'd)

Stereotypic Behavior	6, 11, 17, 27, 35, 45, 49	Stereotypic Behavior	6, 11, 17, 27, 35, 45, 49	7 out of 7 (100%)
Hyperactivity/ Noncompliance	1, 7, 13, 15, 18, 21, 24, 28, 31, 38, 39, 44, 48, 51, 54, 56,	Hyperactivity	1, 7, 13, 15, 21, 31, 38, 39, 48, 54	10 out of 16 (63%) Missing Items 18, 24, 28, 44, 51, 56
Inappropriate Speech	9, 22, 33, 46	Inappropriate Speech	9, 22, 33, 46	4 out of 4 (100%)

Ninety-three percent or 14 out of 15 items in the Irritability factor in Aman and Singh (2017) and the Self-Injury/Irritability factor in the FFSEFA overlapped between them. The FFSEFA Self-Injury/Irritability factor contained one additional item (item 18) and was missing one item (item 25) compared to the Aman and Singh (2017) Irritability factor. The FFSEFA Social Withdrawal/Noncompliance factor contained 100% of the items, or 16 out of 16, found in the Aman and Singh (2017) Social Withdrawal factor; however the FFSEFA also included items 5, 24, 25, 28, and 44. One hundred percent of the items, or seven out of seven, were found in the Aman and Singh (2017) Stereotypic Behavior factor and the FFSEFA Stereotypic Behavior factor. One hundred percent of items, or four out of four, were found in the Aman and Singh (2017) Inappropriate Speech factor and the FFSEFA Inappropriate Speech factor. The Hyperactivity factor in the FFSEFA maintained 63% of the items in the Hyperactivity/Noncompliance factor in the Aman and Singh (2017) model. The items that were not in the FFSEFA Hyperactivity factor (18, 24, 28, 44, 51, 56) were all found in the FFSEFA Social Withdrawal/Noncompliance factor except for item 18, which, as stated previously, was found in the Self Injury/Irritability factor. In total 51 out of 58 items (88%) from the Aman and Singh (2017) model were found in the same factors as in the FFSEFA.

Research question 4 summary. A quantitative benchmark was not created to specifically assess the degree to which the five-factor solution derived in the study one EFA matched the ABC-C test authors' five-factor solution. However, a qualitative examination revealed a high degree of similarity in terms of factor names, highest loading items that helped to name the factor, and the number of overlapping items that were found in each factor. Therefore, it appears that hypothesis 4 was fully supported in that the two, five-factor solutions were largely similar.

Study Two

Data cleaning and missing data. The dataset for study two was scanned for missing values and extreme outliers before performing the CFA. No unusual values (e.g., values outside of the scaling) or extreme outlier cases were present. All item distributions were non-normal, as expected. Like the dataset in study one, less than 1% of the 243 cases had any missing values—and no case had more than two item values missing. Missing data met the assumption of missing completely at random. As a result, an expectation-maximization method (Allison, 2002) was implemented and missing values were replaced without having to use more rigorous missing data procedures.

Model specification. Multiple CFA models were tested in the CFA analysis. These included a) the nine-factor model derived in study one, b) the four-and five-factor models from Brinkley et al. (2007), originally derived from an ASD sample with parents as raters, c) the seven-factor model from Mirwis (2011), originally derived from an ASD sample with special education staff as raters, and d) the original five-factor model of the ABC from Aman et al. (1985a), which maintains the same factor loadings and factor structure as in the ABC-C supplemental manual from Aman and Singh (1994) and the updated ABC-C2 manual from Aman and Singh (2017) and was originally derived from an institutionalized ID sample rated by

institutional staff members. The six-factor model from Sansone et al. (2012), originally derived from a Fragile X sample rated by caregivers, was also included. In all, the fit of six different CFA models total was assessed (see Appendices A, B, C, D, E, and F for the path diagrams of the tested CFA models).

Model identification. All models in study two were overidentified (see Table 26 for *df* for each model). The fixed factor method was used (i.e., setting all factor variances to 1.0 and allowing factor loadings to be freely estimated using factor variance units). Of note, one item in each model generated a negative residual. This issue was dealt with in the following way. First, each model was assessed with the problematic item loading fixed to 1.0, which set the residual to 0. Second, the item was deleted from the model and the CFA was run a second time. Whether or not the item remained in the model, the difference in fit for the RMSEA, CFI, and TLI was < than .001 (i.e., differing by no more than one in the third decimal place). Thus, keeping the item in the model with a fixed loading of 1.0 or deleting the item from the model did not substantively alter model fit. The fit statistics reported here in the results were from the models that included the item. This involved fixing item 46 (*repeats a word or phrase over and over*) in the Aman et al. (1985a) five-factor model, the Mirwis (2011) seven-factor model, the six-factor Sansone et al. (2012) model, and in the nine-factor model from study one. The item 34 loading (*cries over minor annoyances and hurts*) was also set to 1.0 for the Brinkley et al (2007) four- and five-factor models. Fixing the item 46 loading did not result in a change to the model fit outcomes for the Aman et al. (1985a) model, the Mirwis (2011) model, the Sansone et al. (2012) model or the nine-factor model from study one—when compared to the same model in each case with no fixed factor loadings. Fixing item 34 in the four- and five-factor models in Brinkley et al. (2007) had a negative impact on fit index outcomes; however, the impact was not substantive enough

that it resulted in a markedly different assessment of the models' viability. Follow-up regression analyses suggested that the issue with item 46 and 34 likely resulted from multicollinearity.

Model estimation. Model estimation was conducted using Mplus version 8.2. Due to the ordinal and non-normal nature of the item data distributions, the weighted least squares mean and variance adjusted (WLSMV) estimation approach on the polychoric correlation matrix and sample estimated asymptotic covariance matrix was used in order to assess the fit of the various models. Indices available through WLSMV do not allow for direct comparison of non-nested CFA models in terms of fit. Therefore, for model comparison purposes, the Akaike's Information Criterion (AIC) and the Bayes Information Criterion (BIC), which allow for the assessment of the relative fit of non-nested CFA models within the same variance-covariance matrix, were calculated using the Mplus Robust Maximum Likelihood (MLR) estimator. The WLSMV estimator does not enable generation of the AIC or the BIC fit indices and therefore the MLR estimator was necessary to produce these two fit index outputs. Of note, the Sansone et al. (2012) six-factor model could not be assessed with AIC and BIC fit statistics because of its use of a three-item parcel. The item parcel altered the number of total items in the Sansone et al. (2012) model, rendering the model non-comparable to the other models.

Model fit. Multiple fit indices were generated in order to determine the fit of each individual model to the data and in order to compare the relative fit of five of the six models to each other. (The six-factor model by Sansone et al. [2012] could not be directly compared to the other models because it is based on a different number of observed variables—making the variance-covariance matrix non-equivalent to the one used for the other five models. This occurred because the Sansone et al. six-factor model contains a three-item parcel [made up of the

three self-injury items], which combines the three items into a single observed variable/indicator.)

In this study, three different fit index categories were used, which are often referred to as a) absolute fit indices, b) indices fit adjusted for model parsimony, and c) comparative (incremental) fit indices (Brown, 2006; Byrne, 2012). For the absolute fit indices (as classified by Brown, 2006), a Chi-Square (χ^2) and Standardized Root Mean Square Residual (SRMR) were used. For the parsimony correction indices, as classified by Brown (2006), the Root Mean Square Error of Estimation (RMSEA) was used and, as classified by Byrne (2012) the Akaike's Information Criterion (AIC) and the Bayes Information Criterion (BIC) were used. The AIC and BIC were specifically selected because they are information criterion indices which allow for a direct comparison between two non-nested models using the same set of data (i.e., same variance-covariance matrix). For the comparative fit indices, as classified by Brown (2006), the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) were used. In all, no single index was given more weight than any other. Quality of fit for the various models was ultimately judged based upon the totality of the outcomes from the seven different fit indices. However, only the AIC and BIC were used to directly compare the models to each other in terms of parsimony-corrected relative fit.

Within Mplus version 8.2, WLSMV makes available several fit indices for assessing the fit of individual models (e.g., WLSMV adjusted χ^2, RMSEA, CFI, TLI, SRMR, etc.). However, these fit indices cannot be used for direct model comparison. For model comparison, WLSMV in Mplus offers the DIFFTEST option, which allows assessing the difference between nested models for statistical significance using adjusted likelihood ratios. Given that the CFA models examined in the current study could not strictly be considered nested variants of each other, it

was not legitimate to examine differences in fit between them using the DIFFTEST. For comparing the relative fit of non-nested models within the same data set and using the same observed variables (i.e., same variance-covariance matrix), the AIC and BIC indices are recommended (Byrne, 2012). These indices are not available through WLSMV estimation, but are available in Mplus through the Robust Maximum Likelihood (MLR) estimation method. Evidence from simulation studies clearly indicates that WLSMV is superior to MLR under data conditions present in the current study sample (Li, 2016). This was evident when data from the present study were run through both estimation procedures. Under MLR, the primary fit indices (i.e., χ^2, RMSEA, CFI, TLI, and SRMR) were suggestive of much poorer fit relative to values yielded by the WLSMV algorithm. This made it clear that MLR adjustment was insufficient and would not be useful for this purpose. However, given that AIC and BIC were likely to retain their relative rank across different CFA models for the same variance-covariance matrix, and that these two indices are not available through WLSMV, it was decided to derive primary fit indices through WLSMV but then derive AIC and BIC values through MLR for the present study.

Research question 5. *How does the factor solution generated in a sample of individuals with ASD rated by special education staff members for the ABC-C compare in terms of absolute and relative fit to previous ABC-C factor models found in ASD samples or proposed for use with individuals with ASD? Hypotheses 5a, 5b: the nine-factor ABC-C factor model selected in study one will adequately fit the ABC-C variance-covariance matrix of the second ASD sample, and it will demonstrate a better fit to the second ASD sample than previous ABC-C factor models found in ASD samples or proposed for use with individuals with ASD.* Hypothesis 5a was assessed using the Mplus WLSMV estimator via the WLSMV-adjusted χ^2, SRMR, RMSEA, CFI, and

TLI. (The adequacy of each of the other five CFA models was assessed using this strategy as well.) Hypothesis 5b was assessed primarily by comparing AIC and BIC values across models. AIC and BIC values were generated through the Mplus MLR estimation procedure.

Results for all six models examined across absolute fit indices can be found in Table 26. Absolute fit indices assess if the predicted variance-covariance matrix is equivalent to the sample

Table 26. *CFA Model Results: Absolute Fit Indices*

Model	χ^2	*df*	*p*	SRMR
Brinkley et al. (2007) four-factor model	4674.801	1590	<.001	0.116
Brinkley et al. (2007) five-factor model	3925.658	1586	<.001	0.104
Aman et al. (1985a) five-factor model	3854.660	1586	<.001	0.107
Sansone et al. (2012) six-factor model	3246.261	1469	<.001	0.093
Mirwis (2011) seven-factor model	3627.982	1575	<.001	0.099
Study one nine-factor model	3021.420	1560	<.001	0.083

variance-covariance matrix (Harrington, 2009). A statistically significant result with the WLSMV adjusted χ^2 statistic ($p < .05$) signifies that the hypothesized model does not exactly fit the data. The χ^2 statistic for the nine-factor model was statistically significant ($p < .001$) and thus did not meet criteria for an exact model fit. In addition, all five other models in this study assessed with the χ^2 statistic were also statistically significant ($p < .001$) and therefore failed to meet criteria for model fit. (This result is not unusual in CFA nor in broader structural equation modeling, as χ^2 strictly assesses exact fit and larger sample sizes can render significant what may be trivial model discrepancies [Byrne, 2012]). The Standardized Root Mean Square Residual (SRMR) was also used to determine absolute fit. The SRMR measures how incongruent the hypothesized model is from a perfect fit of 0, with values ranging from 0 to 1. According to Hu

and Bentler (1999), a cutoff value of "close to .08" for the SRMR is recommended (p. 27). The SRMR of the nine-factor model was > .08 but was near the threshold approaching an acceptable fit. The SRMR values of the five other models examined were also > .08, ranging from .99 to .116, although not close enough to the cut-off to fit satisfactorily.

Results for all six models examined across the RMSEA parsimony correction fit index can be found in Table 27. The parsimony correction indices are comparable to absolute fit indices except that degrees of freedom (*df*) are taken into account, resulting in an increasing penalty as the number of freely estimated parameters increases. The Root Mean Square Error of Estimation (RMSEA) was one of the three parsimony correction indices used in study two. The RMSEA measures the level of mis-fit relative to the population, with a perfect fit equivalent to 0. According to Browne and Cudek (1993) values $\leq$ .05 are considered a "close fit," values > .05 and $\leq$ .08 considered a "reasonable" fit, and values $\geq$ .10 are not considered acceptable (p. 144). Hu and Bentler (1999) suggest an RMSEA cut off value close to .06. A 90% confidence interval (CI) was also included for the RMSEA values.

Table 27. *CFA Model Results: RMSEA Parsimony Correction Index*

Model	RMSEA	90% Confidence Interval (CI)
Brinkley et al. (2007) four-factor model	.089	.086- .092
Brinkley et al. (2007) five-factor model	.078	.075- .081
Aman et al. (1985a) five-factor model	.077	.074- .080
Sansone et al. (2012) six-factor model	.071	.067- .074
Mirwis (2011) seven-factor model	.073	.070- .076
Study one nine-factor model	.062	.059- .065

The nine-factor model resulted in an RMSEA of .062 and a CI between .059 and .065. According to Browne and Cudeck (1993) this would be considered a reasonable fitting model,

while according to Hu and Bentler (1999), this model would meet the threshold for fit recommendation. Four of the models (the Brinkley et al. [2007] five-factor model, the Aman et al. [1985a] five-factor model, the Sansone et al. [2012] six-factor model, and the Mirwis [2011] seven-factor model) were all considered reasonable fitting models according to Browne and Cudeck (1993) criteria, although they did not meet the cut off recommendation according to Hu and Bentler (1999). The Brinkley et al. (2007) four-factor model was neither in the reasonable range of fit according to Browne and Cudeck (1993) and nor did it meet the cut off values articulated by Hu and Bentler (1999).

Results for all six models examined across the comparative fit indices can be found in Table 28. The comparative fit indices assess the fit of the hypothesized model compared to a restricted nested model. The Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) were assessed. The CFI ranges between 0 and 1. According to Brown (2006) and Hu and Bentler (1999) values > or close to .95 are considered reasonably well fitting. Brown (2006) also stated that values between .90 and .95 should be considered "marginal," with fit appraisal ultimately determined within the context of the model's fit across the other fit indices as well (p.87).

Table 28. *CFA Model Results: Comparative Fit Indices*

Model	CFI	TLI
Brinkley et al. (2007) four-factor model	0.876	0.871
Brinkley et al. (2007) five-factor model	0.906	0.902
Aman et al. (1985a) five-factor model	0.909	0.905
Sansone et al. (2012) six-factor model	0.909	0.905
Mirwis (2011) seven-factor model	0.917	0.913
Study one nine-factor model	0.941	0.938

The CFI for the nine-factor model approached the .95 cutoff value at .941. The other five models were below the .95 cut off value ranging from .876 to .917. The TLI is similar to the CFI although it includes a penalty for more complex models. The cutoff values are similar to the CFI (Brown, 2006; Hu & Bentler, 1999). The TLI value for the nine-factor model failed to reach to the .95 cutoff value but approached the cutoff at .938, and according to Brown (2006), was within the marginal range of fit. The TLI for the other five models also failed to meet the .95 cutoff value ranging from .871 to .913. The Brinkley et al. (2007) model, the Aman et al. (1985a) model, the Sansone et al. (2012) model, and the Mirwis (2011) model were all within the marginal range of fit according to Brown (2006), although they should all be appraised based upon outcomes across the other fit indices as well.

Research question 5 hypothesis 5a summary. No single fit index was considered determinative of what constituted a reasonable model fit for the nine-factor solution selected in study one. Thus, multiple indices were chosen in order to help gain a thorough picture of how the nine-factor model fared across varying analyses. Based upon results across all three types of fit indices (absolute, parsimony correction, and comparative) it was determined that the nine-factor solution adequately fit the ABC-C variance-covariance matrix of the second sample, thus supporting hypothesis 5a.

AIC and BIC fit indices. Results for the five models examined across the AIC and BIC parsimony correction fit indices can be found in Table 29.

Table 29. *CFA Model Results: AIC and BIC Parsimony Correction Indices*

Model	AIC	BIC
Brinkley et al. (2007) four-factor model	31096.262	31725.013
Brinkley et al. (2007) five-factor model	30710.149	31352.872
Aman et al. (1985a) five-factor model	30936.966	31579.689

Table 29 (cont'd)		
Sansone et al. (2012) six-factor model	*	*
Mirwis (2011) seven-factor model	30173.515	30854.662
Study one nine-factor model	29622.523	30356.066

* AIC and BIC could not be calculated for Sansone et al. (2012) because of the use of an item parcel in its model.

Unlike the other fit indices examined in this study, the AIC and BIC indices enable one to make a direct comparison between non-nested models on the same set of data. The lower the value of the AIC and BIC, the better the fit of the model. The nine-factor model resulted in the lowest value for both the AIC and the BIC compared to all other models with the seven-factor model by Mirwis (2011) the next best fitting model. As previously noted, the Sansone et al. (2012) six-factor model could not be meaningfully compared to the other models using any fit statistics because the use of an item parcel in this model rendered its variance-covariance matrix non-identical to that of the other models. Models based on different variance-covariance matrices for their observed variables cannot be meaningfully compared.

Research question 5 hypothesis 5b summary. To primarily assess hypothesis 5b, AIC and BIC values, generated through the Mplus MLR estimation procedure, were directly compared across five models. Secondarily, although models across the different fit indices generated via the Mplus WLSMV estimator (χ^2, SRMR, RMSEA, CFI, and TLI) could not be directly compared, certain models distinguished themselves as coming closer to meeting adequacy standards than others. Results from the AIC and BIC analysis showed the nine-factor model with the lowest AIC and BIC scores across the five models tested. The nine-factor model also distinguished itself across the other indices as it met or approached cut off values in four of the five fit tests. Thus, it appeared that the nine-factor model demonstrated a better fit than

previously generated ABC-C factor models found in ASD samples or proposed for use with individuals with ASD. Therefore, hypothesis 5b was supported.

In addition to the fit indices generated for the CFA analysis, WLSMV parameter estimates, standard errors, two tailed *p-values*, R^2 *values*, and residual variances were produced. These statistics can be found in Table 30 for the nine-factor model and in Appendices I, J, K, L, and M for the four-and five-factor Brinkley et al. (2007) models, the five-factor Aman et al. (1985a) model, the six-factor Sansone et al. (2012) model and the seven-factor Mirwis (2011) model respectively. In addition, path diagrams for each of the nine factors of the nine-factor model were generated, complete with item loadings and error variances. These can be found in Figures 6 thru 14. Of note, for the sake of visual clarity, each factor and its item loadings were placed on a single page. As a result correlations between factors were not illustrated, despite the fact that all factors were correlated. Inter-factor correlations generated from the CFA analysis are detailed in Table 31.

Table 30. *Study Two CFA Nine-Factor Model Parameter Estimates, Standard Errors, Two-Tailed p-Value, R^2, Residual Variance*

Factor	Item #	Item String	Parameter Estimate	Standard Error (S.E.)	Parameter Estimate/ Standard Error (S.E.)	Two-Tailed *p*-value	R^2	Residual Variance
Hyperactivity								
	7	Boisterous (inappropriately noisy and rough)	0.947	0.022	43.855	< .001	0.896	0.104
	54	Tends to be excessively active	0.905	0.019	47.644	< .001	0.820	0.180
	15	Restless, unable to sit still	0.897	0.019	47.520	< .001	0.805	0.195

Table 30 (cont'd)

	38	Does not stay in seat (e.g., during lesson or training periods, meals, etc.)	0.897	0.022	40.064	< .001	0.804	0.196
	48	Constantly runs or jumps around the room	0.885	0.025	35.392	< .001	0.784	0.216
	39	Will not sit still for any length of time	0.875	0.026	33.996	< .001	0.766	0.234
	1	Excessively active at home, school, work, or elsewhere	0.867	0.023	38.121	< .001	0.751	0.249
	13	Impulsive (acts without thinking)	0.864	0.030	29.201	< .001	0.747	0.253
Stereotypic Behavior								
	17	Odd, bizarre in behavior	0.965	0.030	32.338	< .001	0.931	0.069
	11	Stereotyped behavior; abnormal, repetitive movements	0.929	0.018	52.640	< .001	0.863	0.137
	6	Meaningless, recurring body movements	0.915	0.018	51.175	< .001	0.837	0.163
	35	Repetitive hand, body, or head movements	0.868	0.021	41.203	< .001	0.754	0.246
	27	Moves or rolls head back and forth repetitively	0.814	0.047	17.490	< .001	0.663	0.337
	45	Waves or shakes the extremities repeatedly	0.811	0.033	24.799	< .001	0.657	0.343
	49	Rocks body back and forth repeatedly	0.770	0.047	16.552	< .001	0.594	0.406

Table 30 (cont'd)								
Self-Injury/ Aggressiveness								
	50	Deliberately hurts himself/herself	0.992	0.005	181.907	< .001	0.983	0.017
	47	Stamps feet or bangs objects or slams doors	0.978	0.041	23.561	< .001	0.956	0.044
	2	Injures self on purpose	0.962	0.007	131.495	< .001	0.925	0.075
	52	Does physical violence to self	0.959	0.008	115.483	< .001	0.920	0.080
	4	Aggressive to other children or adults (verbally or physically)	0.867	0.040	21.850	< .001	0.752	0.248
Social Withdrawal								
	30	Isolates himself/herself from other children or adults	0.957	0.013	71.262	< .001	0.916	0.084
	16	Withdrawn; prefers solitary activities	0.916	0.019	49.108	< .001	0.839	0.161
	5	Seeks isolation from others	0.902	0.018	49.258	< .001	0.814	0.186
	42	Prefers to be alone	0.873	0.022	39.082	< .001	0.762	0.238
	58	Shows few social reactions to others	0.848	0.036	23.304	< .001	0.718	0.282
	55	Responds negatively to affection	0.778	0.061	12.806	< .001	0.605	0.395
Inappropriate Speech								
	46	Talks excessively	1.000	.000	[a]	[a]	1.000	.000
	22	Talks to self loudly	0.896	0.026	34.004	< .001	0.803	0.197

Table 30 (cont'd)								
	33	Repeats a word or phrase over and over	0.831	0.053	15.772	< .001	0.690	0.310
	9	Repetitive speech	0.705	0.056	12.663	< .001	0.497	0.503
Lethargy								
	12	Preoccupied; stares into space	0.868	0.038	22.587	< .001	0.753	0.247
	32	Sits or stands in one position for a long time	0.816	0.042	19.536	< .001	0.666	0.334
	20	Fixed facial expression; lacks emotional responsiveness	0.809	0.043	18.829	< .001	0.654	0.346
	25	Depressed mood	0.729	0.062	11.685	< .001	0.532	0.468
	53	Inactive, never moves spontaneously	0.700	0.067	10.488	< .001	0.489	0.511
	23	Does nothing but sit and watch others	0.609	0.062	9.905	< .001	0.371	0.629
	3	Listless, sluggish, inactive	0.537	0.066	8.106	< .001	0.288	0.712
Irritability/ Tantrums								
	10	Temper tantrums / outbursts	0.921	0.016	57.968	< .001	0.849	0.151
	36	Mood changes quickly	0.908	0.022	41.164	< .001	0.825	0.175
	19	Yells at inappropriate times	0.893	0.021	43.042	< .001	0.797	0.203
	57	Has temper outbursts or tantrums when he/she does not get own way	0.889	0.020	44.941	< .001	0.790	0.210

Table 30 (cont'd)

41	Cries and screams inappropriately	0.876	0.024	36.108	< .001	0.768	0.232
8	Screams inappropriately	0.873	0.023	38.469	< .001	0.762	0.238
29	Demands must be met immediately	0.871	0.024	35.669	< .001	0.759	0.241
14	Irritable and whiny	0.828	0.028	29.571	< .001	0.685	0.315
34	Cries over minor annoyances and hurts	0.731	0.038	19.250	< .001	0.535	0.465
Noncompliance							
56	Deliberately ignores directions	0.887	0.028	31.326	< .001	0.786	0.214
51	Pays no attention when spoken to	0.879	0.020	43.699	< .001	0.772	0.228
28	Does not pay attention to instructions	0.873	0.024	36.542	< .001	0.761	0.239
37	Unresponsive to structured activities (does not react)	0.855	0.031	27.824	< .001	0.731	0.269
40	Is difficult to reach, contact, or get through to	0.815	0.033	24.777	< .001	0.665	0.335
43	Does not try to communicate by words or gestures	0.764	0.044	17.506	< .001	0.583	0.417
44	Easily distractible	0.734	0.040	18.580	< .001	0.539	0.461
Oppositionality							
24	Uncooperative	0.918	0.016	56.586	< .001	0.843	0.157

Table 30 (cont'd)

18	Disobedient; difficult to control	0.909	0.018	50.521	< .001	0.826	0.174
31	Disrupts group activities	0.880	0.019	46.179	< .001	0.774	0.226
21	Disturbs others	0.837	0.026	32.175	< .001	0.700	0.300
26	Resists any form of physical contact	0.687	0.053	13.085	< .001	0.472	0.528

[a] Indicates a factor loading fixed to 1.0 because of a near zero, negative residual.

Figure 6. Path diagram of the Hyperactivity factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

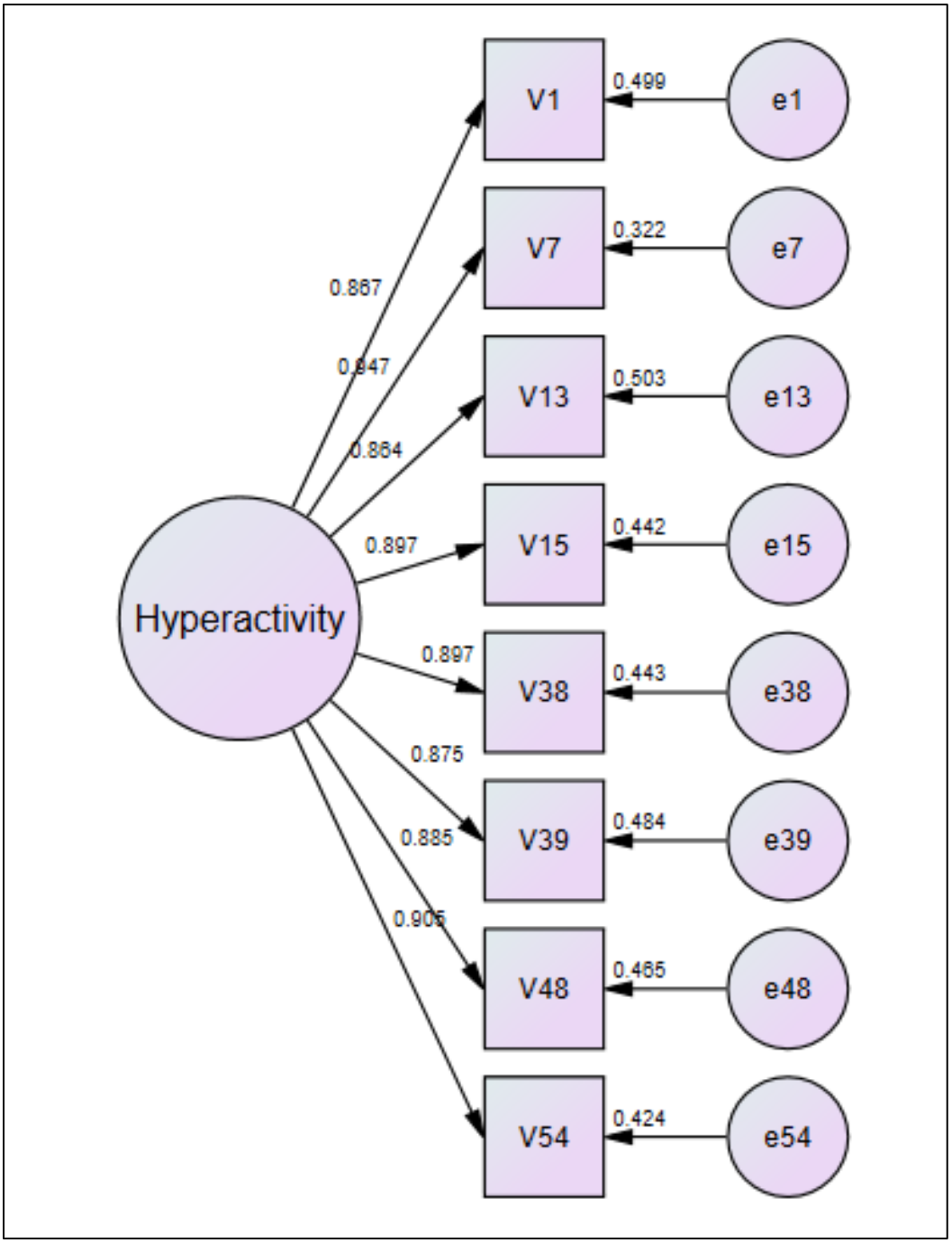


Figure 7. Path diagram of the Stereotypic Behavior factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

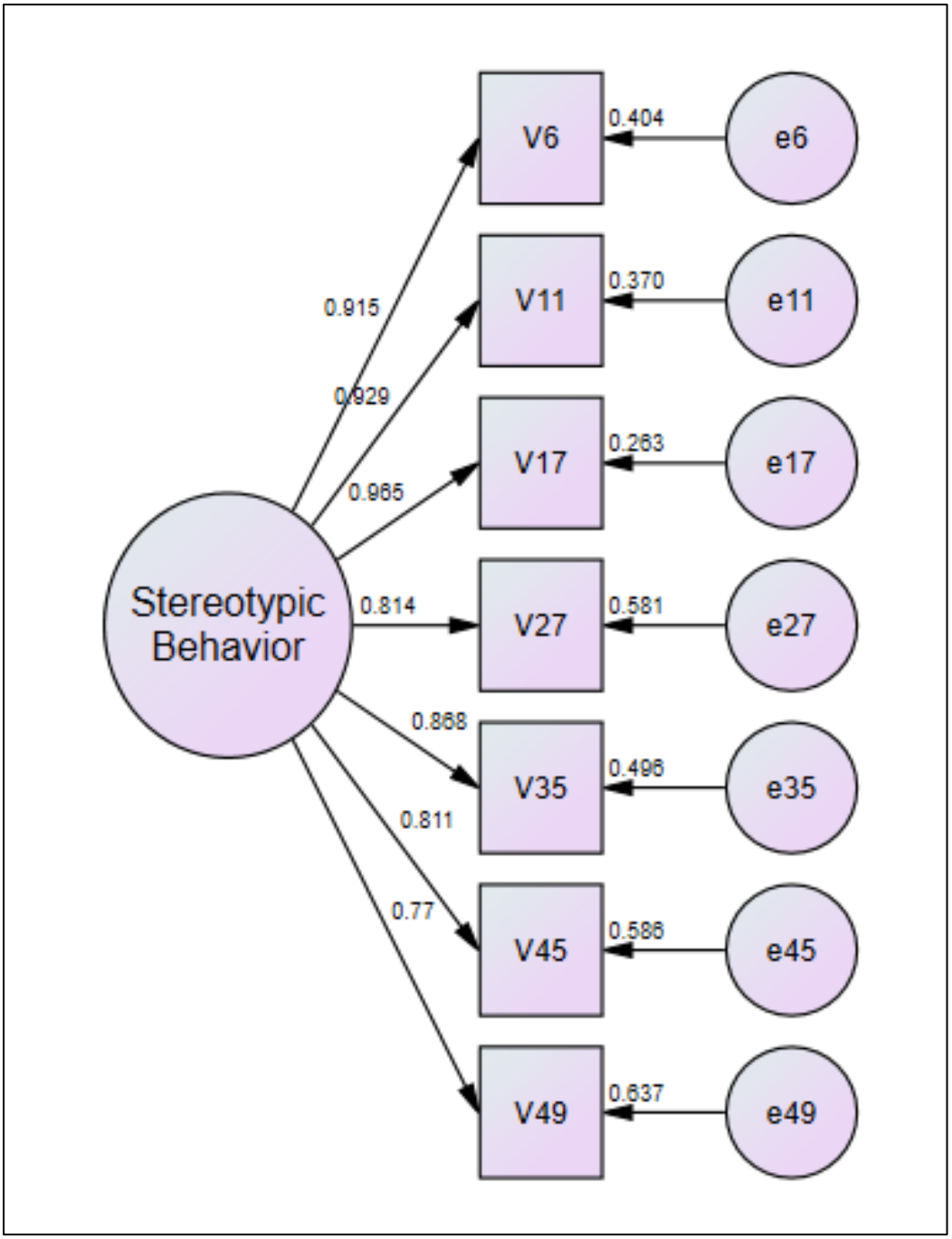


Figure 8. Path diagram of the Self-Injury/Aggressiveness factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

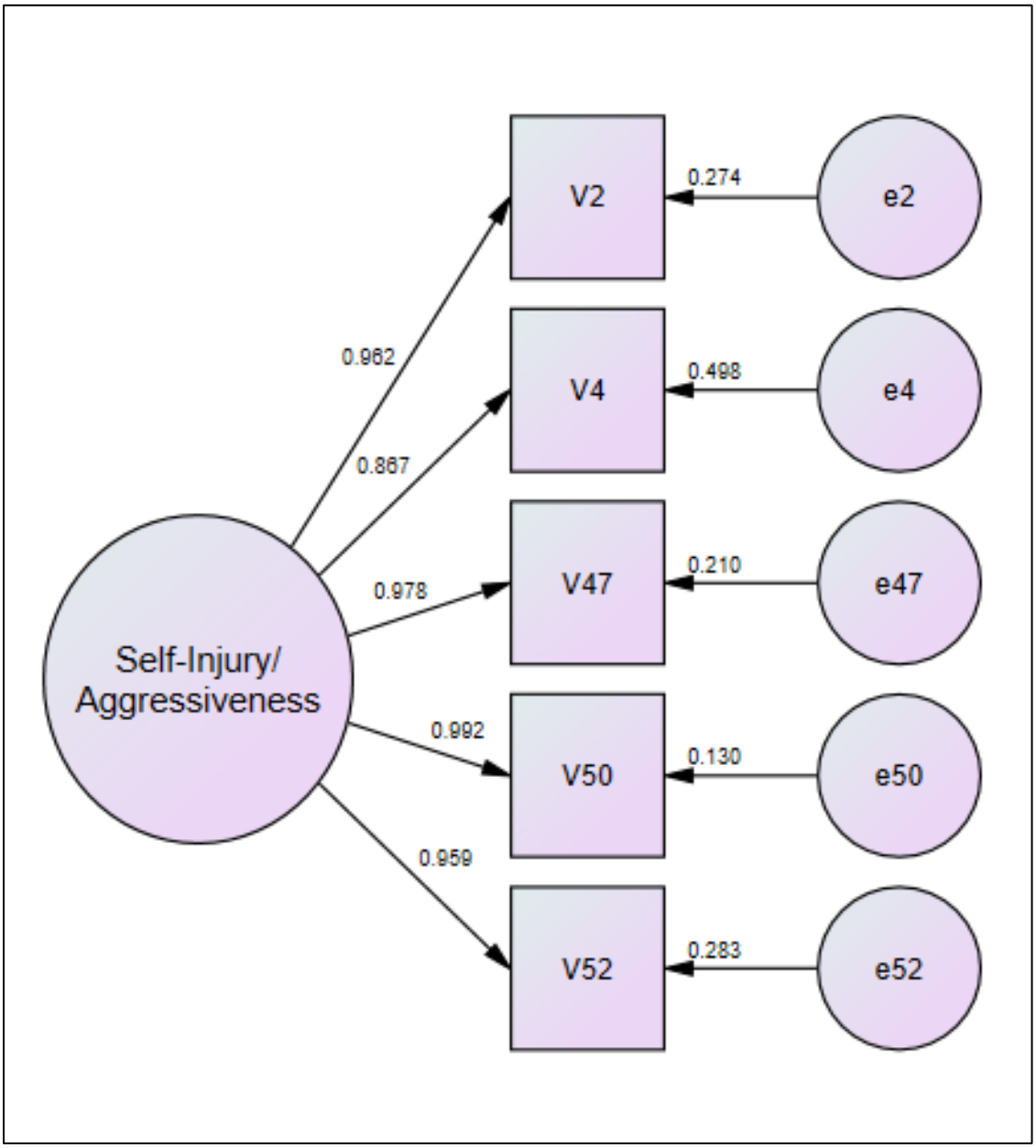


Figure 9. Path diagram of the Social Withdrawal factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

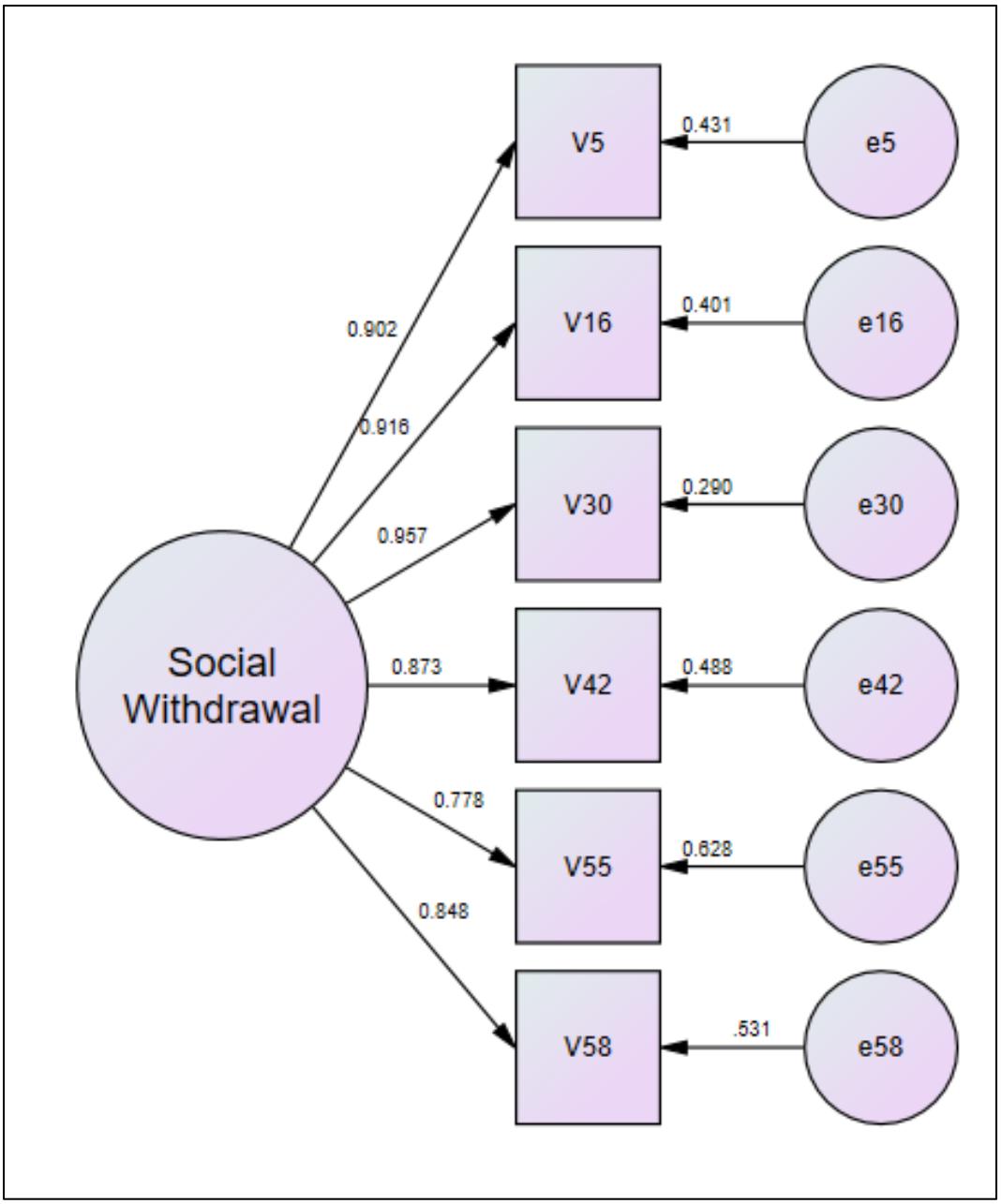


Figure 10. Path diagram of the Inappropriate Speech factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

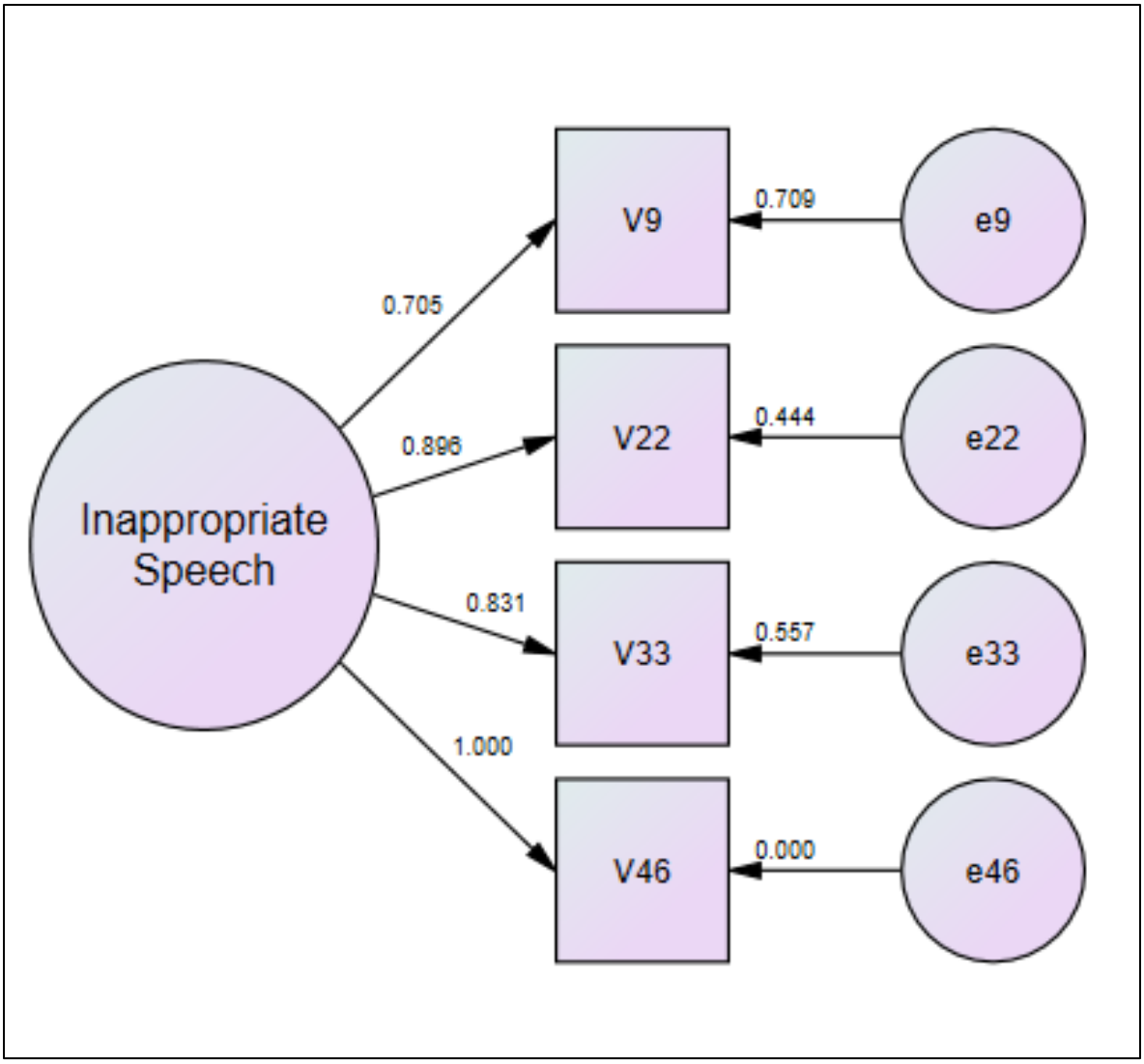


Figure 11. Path diagram of the Lethargy factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

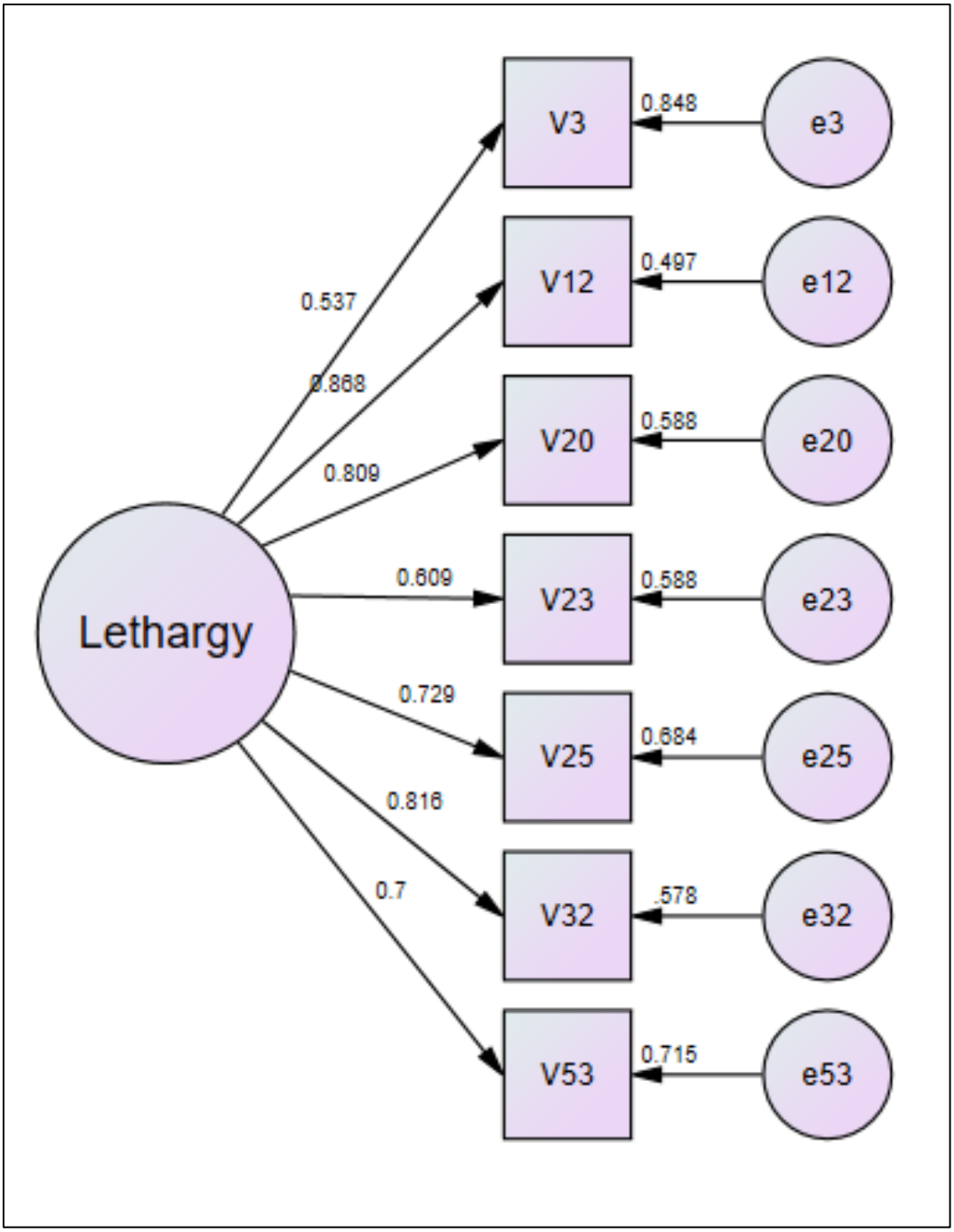


Figure 12. Path diagram of the Irritability/Tantrums factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

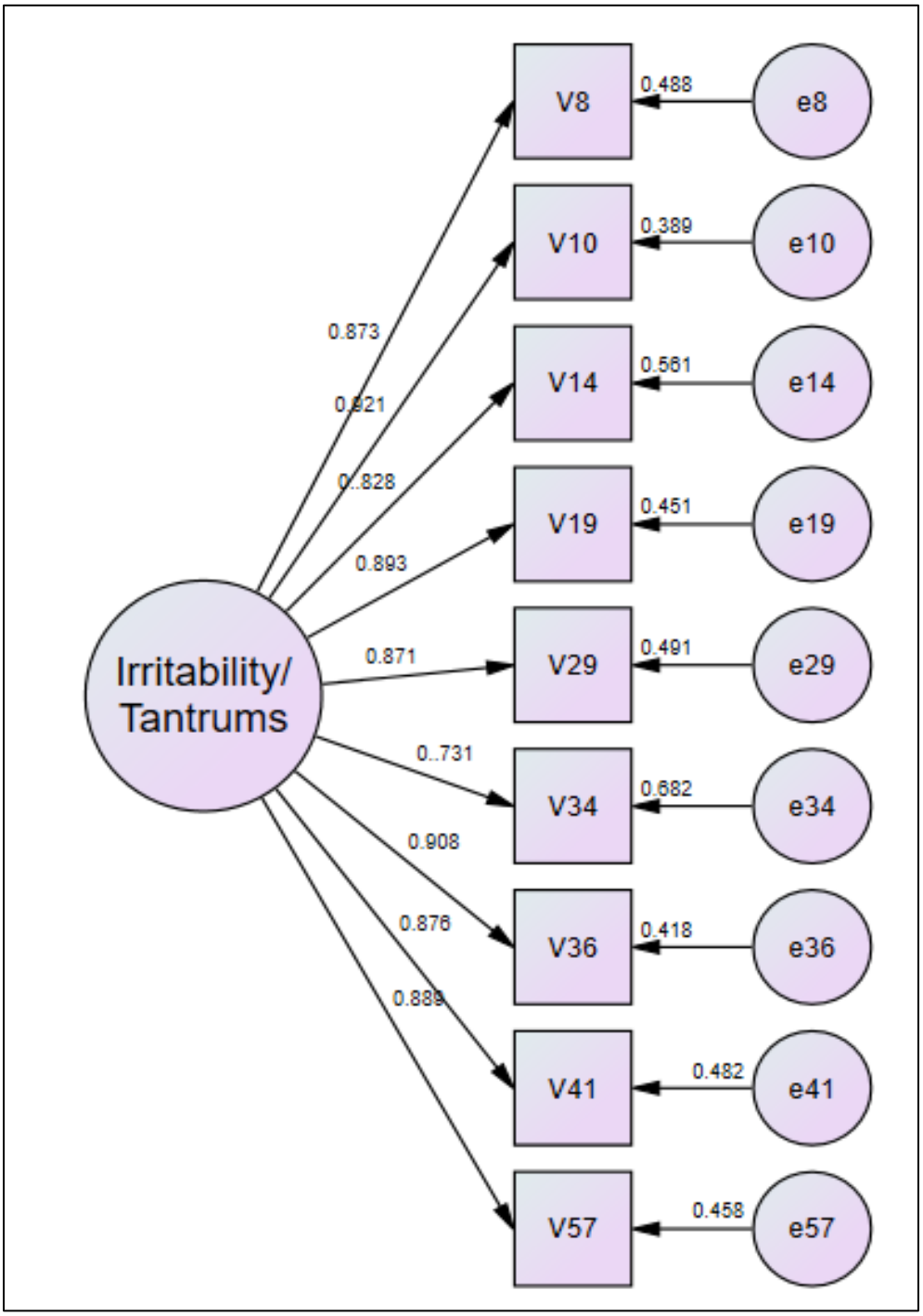


Figure 13. Path diagram of the Noncompliance factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

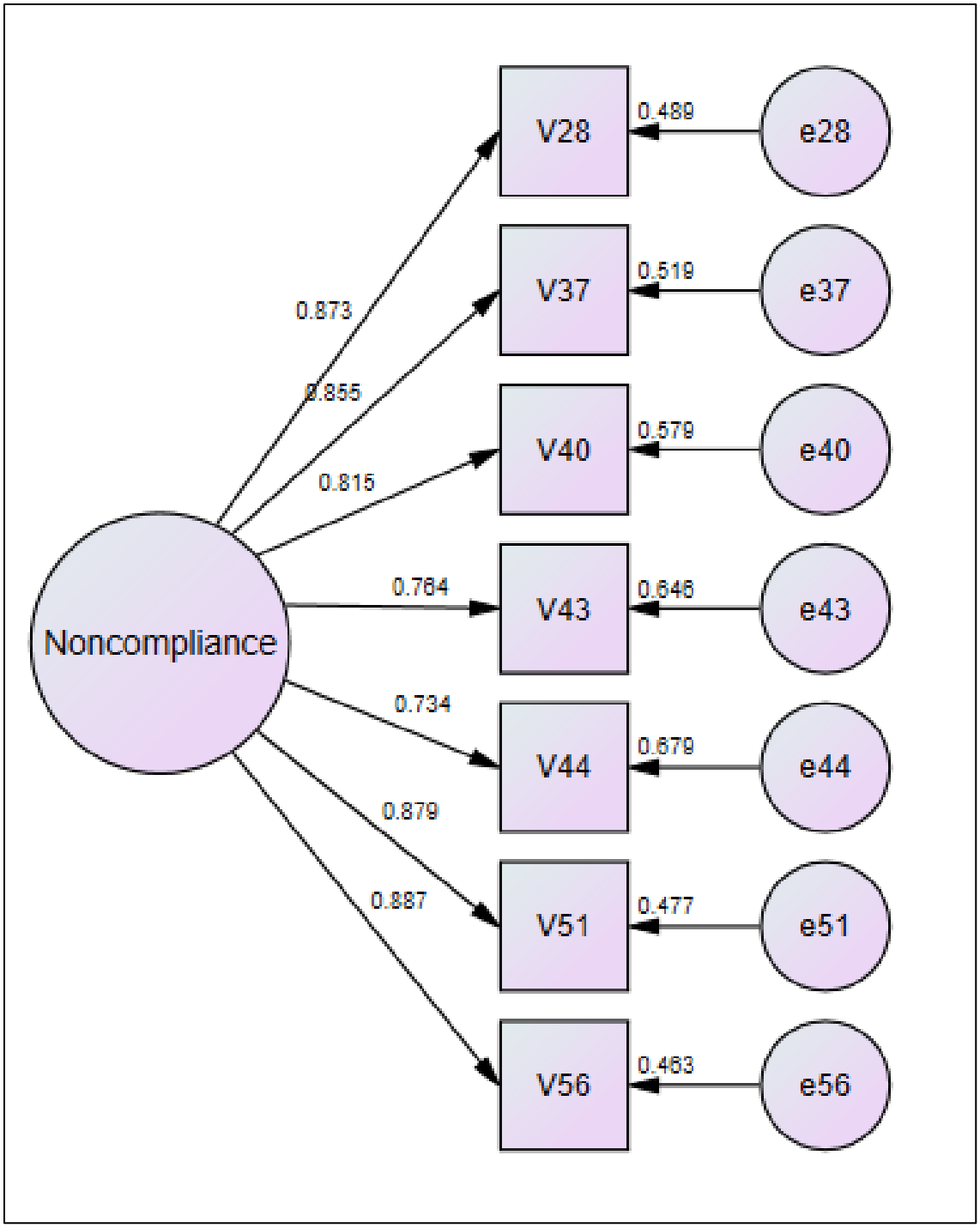


Figure 14. Path diagram of the Oppositionality factor from the nine-factor model with factor loadings and residuals (i.e., random error and unique variation)

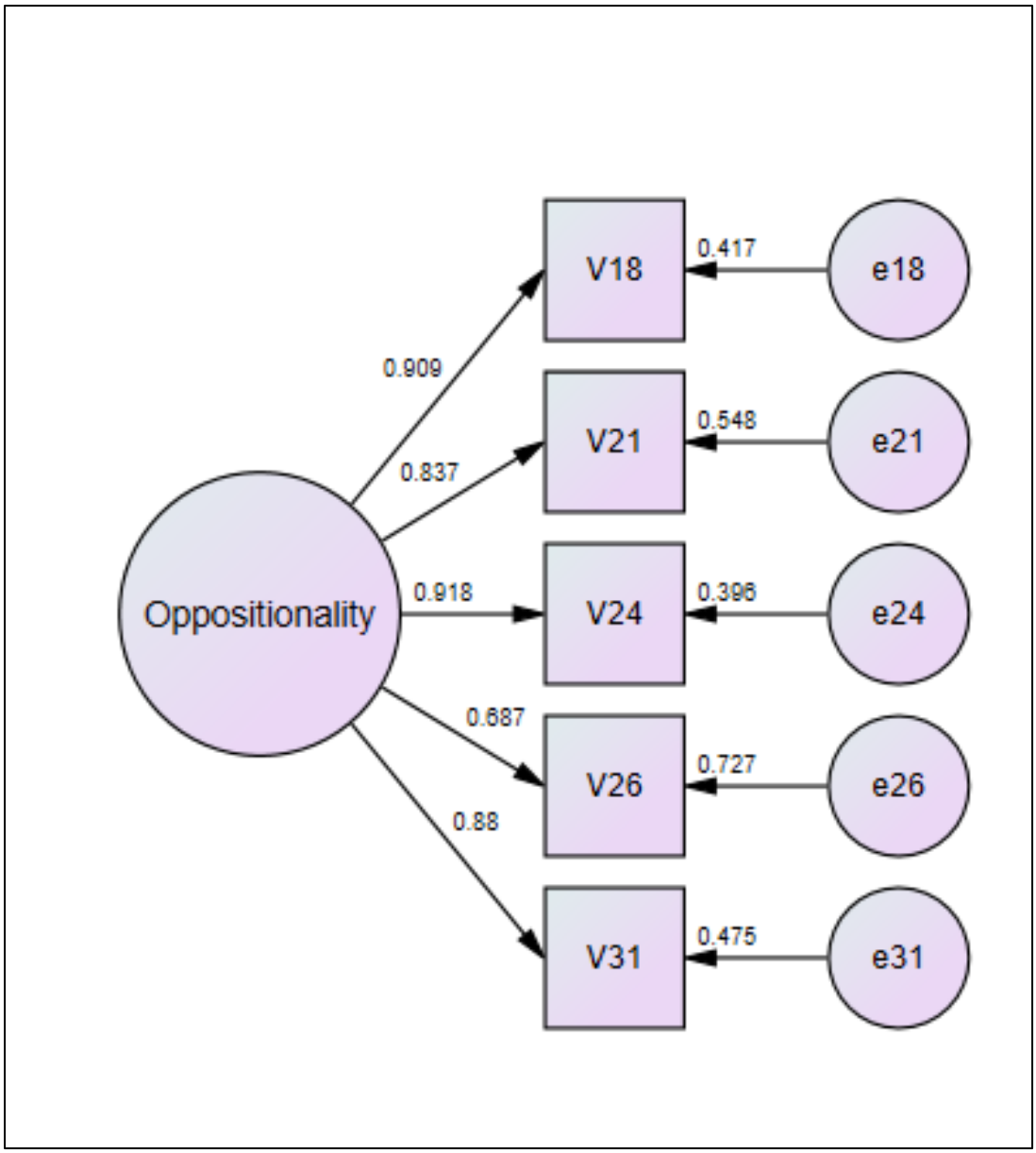


Table 31. *CFA Inter-Factor Correlation Matrix Nine-Factor Solution*

		Factor								
		I	II	III	IV	V	VI	VII	VIII	IX
Factor	I: Hyperactivity	1.000								
	II: Stereotypic Behavior	**0.641**	1.000							
	III: Self-Injury/Aggressiveness	**0.581**	**0.550**	1.000						
	IV: Social Withdrawal	**0.430**	**0.552**	**0.360**	1.000					
	V: Inappropriate Speech	**0.381**	**0.350**	0.208	**0.362**	1.000				
	VI: Lethargy	**0.364**	**0.625**	**0.430**	**0.778**	0.299	1.000			
	VII: Irritability/Tantrums	**0.749**	**0.541**	**0.752**	**0.533**	**0.392**	**0.535**	1.000		
	VIII: Noncompliance	**0.628**	**0.686**	**0.513**	**0.728**	0.282	**0.848**	**0.626**	1.000	
	IX: Oppositionality	**0.815**	**0.622**	**0.678**	**0.623**	**0.450**	**0.585**	**0.874**	**0.777**	1.000

Non-identity values that are ≥ 0.30 are presented in bold print.

Inter-factor correlations resulted in all values ≥ .30 except in three cases: factor V (Inappropriate Speech) with factor III (Self-Injury/Aggressiveness), factor V with factor VI (Lethargy), and factor VIII (Noncompliance) with factor V. Multiple correlations were also in the higher range (≥ .70) including factor VII (Irritability/Tantrums) with factor I (Hyperactivity), factor IX (Oppositionality) with factor I, factor VII with factor III, factor VI with factor IV (Social Withdrawal), factor VIII with factor IV, factor VIII with factor VI, factor IX with factor VII, and factor IX with factor VIII. In addition, various correlations were in the moderate to high range (i.e., ≥ .50 ≤ .70).

CHAPTER 5: DISCUSSION

Overview of Study One and Study Two

The purpose of this study was to examine the factor structure of the Aberrant Behavior Checklist Community (ABC-C) using an autism spectrum disorder (ASD) sample rated by special education staff members. The ABC-C potentially fills a major need for ASD researchers as one of the few instruments capable of assessing treatment effects in individuals with ASD (Lord et al., 2014). However, the ABC-C was originally designed for the ID population and had not been first factor analyzed for the ASD population until 2007 (Brinkley et al., 2007). This occurred years after it had already been used as a primary outcome measure in highly consequential studies for individuals with ASD (e.g., McCracken et al., 2002; Shea et al., 2004) and had become the most frequently used outcome instrument for measuring cognitive and behavioral symptoms in individuals with ASD (Bolte & Diehl, 2013). Since Brinkley et al. (2007) performed the first factor analyses on the ABC-C with an ASD population, Mirwis (2011) followed with an exploratory factor analysis (EFA), and Kaat et al. (2014) performed both an EFA and a confirmatory factor analysis (CFA) of the instrument with ASD samples. Results from these three studies differed, raising questions regarding the most appropriate factor structure of the ABC-C for an ASD population. However, a more thorough examination of the factor analyses by Brinkley et al. (2007), Mirwis (2011), and Kaat et al. (2014) revealed certain questionable methodological choices and skepticism of their drawn conclusions.

Brinkley et al. (2007) performed two factor analyses (exploratory and confirmatory) with the ABC-C in an ASD sample with parents as raters. The exploratory analysis resulted in the authors deciding that both a four-factor solution (Hyperactivity/Noncompliance, Lethargy/Social Withdrawal, Stereotypy, and Irritability) and a five-factor solution

(Hyperactivity/Noncompliance, Lethargy/Social Withdrawal, Stereotypy, Irritability, and Inappropriate Speech) were potentially viable, concluding that their factor models were similar to the solutions found in previous factor analyses of the ABC-C with non-ASD samples (e.g., the Aman et al. [1985a] five-factor model and the four-factor Marshburn and Aman [1992] model). One of the more unique findings in Brinkley et al. (2007) was the emergence of the three self-injurious behavior items loading separately on their own factor (named Irritability) in both the four- and five-factor models. Brinkley et al. (2007) also performed a confirmatory analysis with their derived five-factor solution though it did not result in an acceptable model fit. Despite the conclusions that Brinkley et al. (2007) drew from their study, multiple methodological weaknesses were apparent in their analyses.

The authors used a principal components analysis with an oblique rotation to derive their factor solution, which was more appropriate for data reduction (i.e., reducing the number of observed variables in a dataset) rather than identifying latent constructs reflected in the covariation of the observed variables as in an EFA. The authors also only examined a four- and five-factor solution, failing to explore other possible solutions. In addition, Brinkley et al. (2007) only used the Guttman-Kaiser Criterion and the scree test as their factor retention tests rather than including more robust techniques such as the MAP test (Velicer, 1976) or parallel analysis (Horn, 1965). Finally, the CFA run by Brinkley et al. (2007) was performed on the same sample already used for in their principal components analysis, meaning that their EFA and CFA were not performed on independent samples. In sum, these methodological shortcomings call into question the robustness of the Brinkley et al. (2007) results.

Mirwis (2011) carried out a psychometric study of the ABC-C and set out to improve upon the Brinkley et al. (2007) analyses. Mirwis (2011) performed an EFA using the principal

axis factoring (PAF) method on the ABC-C with an ASD sample (as well as concurrent validity analyses) and used special education staff members as raters. This study involved examination of a wider range of factor solutions (between five and eight factors) compared to Brinkley et al. (2007) and included a parallel analysis along with the Guttman-Kaiser Criterion and scree test to determine how many factors to retain. Mirwis (2011) chose a seven-factor solution (Irritability, Hyperactivity, Withdrawal, Lethargy, Stereotyped Behaviors, Inappropriate Speech, Self-Injurious Behavior) which saw the Lethargy/Social Withdrawal factor in the Aman and Singh (1994) five-factor ABC-C model split into two factors and, similarly as in Brinkley et al. (2007), the emergence of a Self-Injurious Behavior factor. Despite performing a more rigorous analysis than Brinkley et al. (2007), one major methodological weakness stood out in the Mirwis (2011) study.

Mirwis (2011) did not use a polychoric correlation matrix (and instead used a Pearson correlation-matrix) in his EFA, which would be more appropriate for use with the ordinal item data from the ABC-C. This could have attenuated the strength of the correlations between variables, which could have impacted the factors and the loadings. It must also be pointed out that because Mirwis (2011) used special education staff as raters in his study, it is unknown what effect this difference might have had on his results in comparison to caregiver raters.

Kaat et al. (2014) performed the most recent factor analyses of the ABC-C prior to this study, including an EFA and a CFA in an ASD sample with parents as raters. Like Mirwis (2011), Kaat et al. (2014) used PAF in their EFA along with an oblique rotation. However, unlike both Mirwis (2011) and Brinkley et al. (2007), Kaat et al. (2014) used a polychoric correlation matrix as input. Kaat et al. (2014) chose a five-factor solution after their EFA (Irritability, Lethargy/Social Withdrawal, Stereotypic Behavior, Hyperactivity/Noncompliance,

and Inappropriate Speech), which was virtually the same as the existing ABC-C five-factor model (Aman & Singh, 2017). The authors also performed a CFA with an independent sample. They examined the original five-factor solution from the ABC test authors (Aman et al., 1985a) as well as the four-factor solution with an ID sample from Brown et al. (2002), the four- and five-factor solutions from Brinkley et al. (2007), and the six-factor solution found in a Fragile X sample from Sansone et al. (2012). Results from the CFAs did not lead to any model clearly distinguishing itself as fitting well or as the best fitting model. As a result, Kaat et al. (2014) concluded that the original five-factor model from Aman et al. (1985a)—the same model, except for a few item word changes and factor name changes as the ABC-C (Aman & Singh, 1994, 2017)—should be conservatively retained in the absence of evidence for a better model for use with an ASD sample. However, a detailed examination of their study revealed some key methodological weaknesses.

Kaat et al. (2014) only used the Guttman Kaiser Criterion, the scree test, and clinical meaningfulness to determine their factor solution, leaving out some of the more powerful factor retention tests like parallel analysis and the MAP test. This omission could have led Kaat et al. (2014) to look at a more narrow range of potential factor solutions— a four-, five-, and six-factor model—before they decided upon their chosen five-factor solution. Finally, Kaat et al. (2014) decided on the five-factor solution for the ASD population by taking a "historical and pragmatic perspective" (p. 1107) rather than potentially challenge or try and further improve upon the original model. Despite the inclusion of the CFA, which did not provide greater clarity on the most appropriate factor structure for the ABC-C with an ASD population, the Kaat et al. (2014) study seemed to raise even more questions, further increasing the need for a more thorough analysis of the ABC-C in ASD samples.

Thus, the current study attempted to rectify some of the various weaknesses in the previous three factor analyses of the ABC-C with ASD samples. The intention was to better explore possible factor structures for the ABC-C in an ASD sample and to potentially determine the most appropriate factor structure(s) for the scale in the ASD population. To achieve these ends, this research study was broken up into two different studies: study one, and study two.

Study one included performing an EFA on the ABC-C with an ASD sample with special education staff as raters. It was carried out in order to contribute a rigorous study to the limited number of existing studies in the literature. This involved performing a thorough exploratory factor analytic process. This included using the most effective available methods to guide the factor retention process, and relying upon the results and underlying theoretical understanding of the ASD population rather than precedent to determine the most appropriate factor structure in terms of interpretability, explanatory power, meaningful distinctions, and potential clinical utility.

Study two involved a CFA on the ABC-C with an ASD sample as a way to determine both the absolute and relative fit of the model generated in study one and compare it to the existing ABC-C factor analytic models in the literature for the ASD population. It is noteworthy that unlike prior CFAs for the ABC-C with an ASD sample, the CFA in study two included the model derived in the dissertation by Mirwis (2011) and utilized fit indices that enabled a direct comparison between non-nested models. In all, this study was intended to fill in some major gaps in the existing factor analytic literature of the ABC-C for the ASD population and more thoroughly explore the instrument's internal structure validity when rated by special education staff.

The discussion of the findings in study one and study two will be carried out separately. Summary and interpretation sections will be provided. Limitations, implications, and future research implications for each study will also be addressed.

Summary and Interpretation of Findings for Study One

Research question 1 and hypothesis 1. Research question 1 focused on the number of potential interpretable ABC-C factors that would be considered for retention after the EFA was performed. Four factor retention methods were used: the Guttman-Kaiser Criterion, the scree test, parallel analysis, and Velicer's MAP test. Results from the Guttman-Kaiser Criterion suggested eight factors should be retained, while results from the scree test suggested three or five factors should be retained. Plus or minus two factors above and below the parallel analysis and MAP test were considered (as well as the results of the scree test and the Guttman-Kaiser Criterion) resulting in a range of between three and 11 factors that were ultimately assessed for retention. It was hypothesized that between four and seven factors would be available for retention. Given the three- to 11-factor solution range, this hypothesis was not supported.

The hypothesis that a range between four and seven possible factor solutions would be considered for retention was based solely on the existing literature of the ABC-C with an ASD sample (Brinkley et al., 2007; Kaat et al., 2014; Mirwis, 2011). Factor solutions from the three factor analyses of the ABC-C with an ASD sample have ranged between four and seven factors. Results from research question 1 thus went beyond this range, going below and above what was hypothesized. Having a greater number of possible factor solutions than had been considered in the previous literature thus opened up the possibility that a unique factor solution model could be generated from the study one EFA.

It must be acknowledged, as Osborne (2014) points out, no factor retention test is perfect. This resulted in the decision to use multiple retention tests as criteria as well as to explore a range of factors below and above the derived factor test solutions. This was done to ensure that the final factor solution that would ultimately be decided on in study one would be chosen through a process that was highly rigorous. Ultimately, the decision to explore a wide-range of possible solutions was data driven.

The range of factor solutions considered in Mirwis (2011) most closely aligns with the results found for research question 1 of the present study. Mirwis (2011) examined a range of four different solutions, consisting of between five and eight factors, and used three of the same factor retention decision tests for guidance that were used in this study: the Guttman Kaiser Criterion, the scree test, and parallel analysis. The parallel analysis in Mirwis (2011) suggested seven factors for retention, while in this study it designated six factors. Thus, the parallel analysis in Mirwis (2011) and in this study both suggested factor solutions for an ASD sample greater than the current author version of the ABC-C and led to a larger range of factor solutions to consider. Parallel analysis (and the MAP test for that matter) is considered a more accurate and powerful factor retention decision test (e.g., Hayton, Allen, & Scarpello, 2004). Both the parallel analysis and MAP tests in the present study—as well as the parallel analysis results in Mirwis (2011)—suggested the presence of more than five factors, providing reasonably consistent evidence than a viable factor structure within the ASD population likely consists of more than the five factors proposed by the authors of the ABC-C.

Unlike the EFA in this study, Kaat et al. (2014) only used the scree test, the Guttman Kaiser Criterion, and clinical meaningfulness to guide their factor retention decisions, while Brinkley et al (2007) only used the scree test and the Guttman Kaiser Criterion. As a result, Kaat

et al. (2014) only looked at possible solutions ranging between four and six factors while Brinkley et al. (2007) looked only at four- and five-factor solutions. Kaat et al. (2014) reported that the scree plot in their study indicated that five factors should be retained while the Guttman Kaiser Criterion actually showed 11 eigenvalues > 1. Kaat et al. (2014) did not explain why they specifically ignored the Guttman Kaiser Criterion, which could have led to a much broader range of solutions to consider, like in the present study. Unfortunately, Brinkley et al. (2007) did not report the results of their factor retention tests. Moreover, the decision by Kaat et al. (2014) and Brinkley et al. (2007) to not use either parallel analysis or the MAP test (or both) quite possibly limited the number of solutions that they considered and potentially, unknowingly, lead them to look only at solutions with too few factors. Similarly, Mirwis (2011) did not make use of the MAP test either, which may have resulted in the examination of a more limited range of options.

Overall, choosing to use four factor retention tests in this study led to more available information and the examination of a broader range of possible solutions for interpretability than any of the previous EFAs of the ABC-C with an ASD sample. However, had the number of possible solutions for consideration been greater, or more limited, or even the same as Brinkley et al. (2007), Kaat et al. (2014), or Mirwis (2011) was not the point. Rather, the fact that the present study undertook a comprehensive, data-driven, exploratory process—one not limited or biased by previous findings—means that there should be fewer questions regarding the rigor of the analytic method with regard to the factor retention process used in this study and more focus placed on its outcomes.

Research question 2 and hypotheses 2a, 2b, and 2c. Research question 2 built on of the results from research question 1 and focused on which of the derived factor solutions for the ABC-C with an ASD sample would be the most interpretable and thereby retained. Pattern

matrices generated following oblique rotation enabled factor models to be compared. Consideration of solutions between three and eleven factors occurred resulting in two standout options in terms of interpretability: the six-factor solution and the nine-factor solution. The six-factor solution had been suggested by the parallel analysis and the nine-factor solution had been suggested by the MAP test. Two researchers independently considered all factor solutions and two additional researchers were included to consider the six- and nine-factor solutions. Consensus between three of the four researchers was reached that the nine-factor solution was the most interpretable. It was hypothesized that a) at least four-factors would likely be retained, b) that an Inappropriate Speech factor would emerge, and c) a Self-Injurious Behavior factor would also emerge. Hypotheses 2a and 2b were both supported. Hypothesis 2c was not supported because a Self-Injurious Behavior factor did not cleanly emerge with only the three self-injurious behavior items loading on the factor. Instead, two other items loaded as well, which broadened the scope of the factor in terms of aggressiveness toward others and objects.

The decision to choose the nine-factor solution was both data- and theory-driven. It was the solution suggested by the MAP test and it appeared to aptly structure the data in the most refined and clinically meaningful way. Narrowed constructs in the nine-factor structure resulted in fewer items loading on the factors, ranging from the four-item Inappropriate Speech factor to the nine-item Irritability/Tantrums factor. Additionally, the nine-factor structure seemed to have streamlined and separately distributed previously discovered constructs in the other EFAs of the ABC-C.

Consideration of clinical meaningfulness was key in selecting the nine-factor solution over the six-factor solution. Two fundamental questions were contemplated in the decision making: a) whether the constructs that emerged in both factor solutions were clearly defined and

consistent with core and associated behaviors of individuals with ASD and b) whether factors represented clinically distinct constructs that could be specifically targeted for intervention or enhance understanding through important distinctions. Perhaps the most significant problem with the six-factor solution was that it emerged with a Self-Injury/Tantrums/Irritability factor. The three self-injurious behavior items all loaded > .91, clearly defining the factor; however, the inclusion of the 10 other items making up the other constructs, tantrums and irritability, made the factor problematic with regard to clinical clarity and utility. Simply put, an individual who performs self-injurious behaviors may not have tantrum behavior nor might their self-injurious behavior be specifically resulting from irritability. As Minshawi et al. (2014) argued, self-injurious behavior can potentially occur for biomedical, genetic, or even other behavioral reasons. An individual who is having a tantrum or showing irritable behaviors may not be engaging in any self-injurious behavior. Further, a specific intervention targeting tantrum behavior (e.g., Matson, 2009) might be different than one targeting self-injurious behavior (e.g., Matson & LoVullo, 2008). As such, a factor too conceptually dense was deemed problematic and not clearly useful in a research or clinical context. In particular, with regard to individuals in the ASD population, self-injurious behavior occurs about 30% more in individuals with ASD than in individuals with other developmental disabilities (Soke et al., 2016). Thus, it is important when working with individuals from the ASD population to be able to make a clear distinction between self-.injurious behavior and other behaviors (e.g., irritability). In contrast, the nine-factor solution resulted in more narrowed constructs and split the self-injurious and irritable behaviors between two different factors (Self-Injury/Aggressiveness and Irritability/Tantrums), allowing for a more conceptually distinct structure.

The other seven factors in the nine-factor solution all represent independent behavioral constructs that are either core behaviors (Social Withdrawal, Stereotypic Behavior) or associated features (Hyperactivity, Inappropriate Speech, Lethargy, Noncompliance, and Oppositionality) of individuals with ASD. Despite the fact that a more expansive factor structure emerged in the chosen model from study one, the solution was conceptually similar to, and broadly inclusive of many of the constructs found within the other existing hypothesized EFA models. Only the Oppositionality factor emerged as a unique construct.

The Inappropriate Speech and Stereotypic Behavior factors in the nine-factor model have been found across all of the EFA models for the ABC-C with an ASD population (except for the four-factor Brinkley et al. [2007] model which did not include Inappropriate Speech). Aside from one extra item in the Stereotypy factor and Inappropriate Speech factor in the five-factor model in Brinkley et al. (2007), both of these factors loaded with the same items as the nine-factor solution. Similarly in Kaat et al. (2014), all but one of the items in their Stereotypic Behavior factor was similar to the same factor in the nine-factor solution. In Mirwis (2011), the Inappropriate Speech factor contained the same items as the nine-factor solution in this study. All of the items found in the Stereotyped Behaviors factor in Mirwis (2011) were found in the Stereotypic Behavior factor in the nine-factor solution. Thus, results from the current study and in the existing studies seem to confirm that the Inappropriate Speech and Stereotyped behavior factors are relatively robust in the ABC-C and have consistently appeared in virtually all models of the ABC-C with an ASD population.

The Mirwis (2011) seven-factor model most closely aligns with the nine-factor solution from this study. The main conceptual difference between Mirwis (2011) and the author version of the ABC-C (Aman & Singh, 1994) was that the Mirwis (2011) model separated the

Withdrawal and Lethargy constructs into two different factors and it distinguished a three-item Self-Injurious Behavior factor from the otherwise intact Irritability factor. (Of note, in 2017, Aman and Singh [2017] removed the Lethargy name from the previously named Lethargy/ Social Withdrawal factor. The item loadings did not change and they did not explain the reasoning behind the name change). The nine-factor model in this study largely follows and expands upon the Mirwis (2011) model. As in Mirwis (2011), the nine-factor model maintained independent factor constructs for hyperactivity, withdrawal (named Social Withdrawal in this study) and lethargy (as well as the Stereotyped Behavior and Inappropriate Speech factors discussed previously). Mirwis (2011) also maintained a separate Self-Injurious Behavior factor in his study, and although the same three items that made up that factor had the highest loadings in the Self-Injury/Aggressiveness factor in the nine-factor solution, two other items loaded with them as well. All of the items in the Irritability/Tantrums factor in the nine-factor model are found in the Irritability factor in Mirwis (2011) and all of the items in the Oppositionality factor in the nine-factor solution are also found in the Irritability factor in Mirwis (2011). In essence, the nine-factor model maintained six of the factors in Mirwis (2011), split the Irritability factor into two different factors, and added a Noncompliance factor, which included two items from the Mirwis (2011) Lethargy factor (43 and 37), one item from the Mirwis (2011) Withdrawal factor (56) and four items from the Mirwis (2011) Hyperactivity factor (28, 40, 44, and 51). The nine-factor model thus streamlined existing factor constructs in Mirwis (2011) and made some narrower meaningful distinctions.

It is important to note that a seven-factor model similar to the Mirwis (2011) model was considered for retention in study one as well. The structure was interpretable but a number of problematic item cross-loadings were present in the solution. Ultimately, the evidence seemed to

show that additional interpretable and meaningful factors were present in the data and that the seven-factor model was likely insufficient.

The nine-factor model generated in study one greatly expanded upon the four- and five-factor structures in the Brinkley et al. (2007) study and the five-factor model from the Kaat et al. (2014) study of the ABC-C for an ASD population. Unlike the rationale used in Kaat et al. (2014), historical precedent of the previous EFAs for the ABC-C did not influence the final factor solution decision in this study; rather, the choice was data-driven and based on clinical meaningfulness with regard to the ASD population. Both a four- and five-factor solution, like in Brinkley et al. (2007) and Kaat et al. (2014), were also considered for this study. However, neither the four- nor the five-factor solution was suggested by the parallel analysis or the MAP test, although the five-factor solution was suggested by the scree test. The four-factor solution was rejected because some of its factors were considered too conceptually difficult to interpret. The factors combined multiple constructs that made them difficult to clearly define, rendering them clinically less meaningful. The five-factor solution maintained multiple crossloadings across all factors and contained two factors (Social Withdrawal/Noncompliance and Self Injury/Irritability) that appeared overly conceptually crowded. Rejecting the four- and five-factor models in favor of the nine-factor model also included the decision to select a more complex model compared to a more parsimonious solution. Underfactoring can lead to difficulty with factor interpretation, while overfactoring can lead to factors with little conceptual significance (Fabrigar et al., 1999). As Fabrigar et al. (1999) explain it is often safer to overfactor, rather than underfactor—although it is best to do neither.

Discovering and then selecting the nine-factor model was not expected. It was not found in the existing literature nor was it hypothesized in this study. Yet, it must be further highlighted

that implementing a rigorous factor-retention process, which included consideration of a larger range of factor solutions, opened up the potential for this new solution. Although more complex than the other models of the ABC-C for an ASD population, the nine-factor model maintains factors that are more conceptually streamlined and clinically meaningful. This expanded model perhaps highlights potential issues with some of the more conceptually bloated factors (e.g., Irritability, Social Withdrawal) from the five-factor models (i.e., Brinkley et al., 2007; Kaat et al. 2014), and revealed a previously unrecognized, somewhat distinct latent construct: Oppositionality. Determination of whether this new model ultimately improves upon the existing models in the literature is a more complicated question. Analyzing inter-factor correlations (addressed in research question 3) helps to assess whether derived factor constructs are more or less similar. Determining the model's level of absolute and relative fit (addressed in study two) was key to assessing whether or not the model is ultimately worthy of further analysis or if it exists as a mere statistical outlier from a broad, exploratory process.

Research question 3 and hypothesis 3. Research question 3 focused on analyzing the strength of the inter-factor correlations in the nine-factor structure. It was hypothesized that there would be correlations > .30 among some of the factors. Results showed that eight of the nine factors maintained substantive correlations with at least one other factor, ranging from .02 to .45. Only the Inappropriate Speech factor failed to generate a substantive correlation with another factor. Thus, hypothesis 3 was fully supported. Internal consistency reliability estimates were also calculated using both ordinal and Cronbach's alpha. Ordinal alpha estimates ranged from .889 to .951 and Cronbach's alpha estimates ranged from .816 to .931.

Inter-factor correlations supported an oblique structure. Correlations in the nine-factor solution ranged from .02 (Lethargy and Inappropriate Speech), where there is virtually no

relationship to .45 (Lethargy and Social Withdrawal), where there is a moderate relationship. None of the correlations were high enough (i.e., > .80) suggesting the possibility of redundant factors measuring the same constructs (Brown, 2006).

Relations between factors should be more or less correlated depending upon their conceptual relations; therefore, factor correlations on the inter-factor correlation matrix offer the opportunity to analyze whether chosen factor constructs make logical sense. Certain factor correlations in particular are worth highlighting. The Inappropriate Speech factor had the lowest correlations with all other factors (i.e., it did not correlate with any factor $\geq$ .30). This seems to make conceptual sense as the particular types of aberrant speech represented in the factor (e.g., repetitive speech, talking loudly), although consistent within the spectrum of possible behaviors found in ASD, are not necessarily behaviors themselves that are core to the symptoms of ASD (APA, 2013). Therefore these behaviors are not consistent across all individual presentations and behaviors of individuals with ASD. On the other hand, the Hyperactivity factor had the most substantive relationships in the matrix, including with Stereotypic Behavior (.43), Self-Injury/Aggressiveness (.41), Irritability/Tantrums (.35), Noncompliance (.38), and Oppositionality (.35). Rates of comorbidity of ADHD and ASD have been found to be between 20% and 70% (Matson et al., 2013), and a study by Matson, Wilkins, and Macken (2008) found that nearly 94% of individuals with ASD exhibited challenging behaviors (e.g., disruptive behaviors, stereotypies, aggression, and self-injurious behaviors) with 63% exhibiting some externalizing challenging behaviors. Thus the strength of the relations between the Hyperactivity factor and the other aforementioned factors seem to be relatively conceptually appropriate for an ASD sample.

The two factors in this model which have not appeared as independent factors in any of the other EFAs involving the ASD population, Noncompliance and Oppositionality, are also worth further analyzing. The Noncompliance factor had substantive correlations with Hyperactivity (.38) and Stereotypic Behavior (.38), while the Oppositionality factor had substantive correlations with Hyperactivity (.35), Self-Injury/Aggressiveness (.34) and Irritability/Tantrums (.30). The strength of these relations would seem to be consistent with the aforementioned research by Matson et al. (2008) and Matson et al. (2013). The Noncompliance factor also had substantive relations with the factors representing more internalizing behaviors including Social Withdrawal (.43) and Lethargy (.31). This also seems to be conceptually viable as Magnuson and Constantino (2011) argue that individuals with ASD are highly susceptible to mood issues such as depression and anxiety given difficulties with social-communication and can manifest in behaviors such as hyperactivity, self-injurious behavior, aggression, mood lability, and catatonia. Additionally, O'Nions et al. (2018) explained, demand avoidant behavior in ASD can often result in escape behaviors. Furthermore, the Noncompliance factor had the weakest correlation with the Inappropriate Speech factor (.19).

The Oppositionality factor also had a weak correlation with Inappropriate Speech (.19). Both of these weak correlations are consistent with the Inappropriate Speech factor across the other seven factors in the model as well. The weakest correlation associated with the Oppositionality factor was with the Stereotypic Behavior factor (.12). Cunningham and Schreibman (2008) argue that stereotypic behavior requires a functional interpretation, and a blanket assumption of its function should not be assumed. As such, the weak relation between the Oppositionality factor and the Stereotypic Behavior factors in this study could thus possibly be interpreted as these constructs being perceived as functionally independent of each other.

It is challenging to make many direct comparisons with the inter-factor correlations found in both Kaat et al. (2014) and Mirwis (2011) because the factor structure of the nine-factor model is more complex than both of the models in their studies. However, certain similar patterns can be discerned. As expected, correlations were much higher in Kaat et al. (2014) in both their calibration and validation samples (.36 to .76 in the calibration sample, and .36 to .76 in the validation sample). This is potentially because factor constructs are much more conceptually dense compared to the nine-factor structure in this study. Similar to the nine-factor model however, the Inappropriate Speech factor in Kaat et al. (2014) has the lowest correlations with the other four factors, ranging from .36 to .54 in the calibration sample and .36 to .54 in the validation sample. The highest inter-factor correlation in both the calibration and validation sample in Kaat et al. (2014) is .76, between the Irritability and the Hyperactivity/Noncompliance factors. This high correlation is potentially a sign that these factors are conceptually overlapping and might possibly benefit from being broken up into more factors, like in the nine-factor model.

The inter-factor correlations in Mirwis (2011) are more similar compared to the nine-factor model, ranging from .05 to .58. Like in the nine-factor model and in Kaat et al. (2014), the lowest correlations across the factors are associated with the Inappropriate Speech factor. The highest correlation in the seven-factor Mirwis (2011) model was between the Lethargy and Withdrawal factors (.58), which is also the highest correlation in the nine-factor solution (.45). The second highest correlation in Mirwis (2011) between the Hyperactivity factor and the Irritability factor (.55) is also the second highest correlation in the nine-factor model (.43) and, as mentioned previously, also the highest correlation in the Kaat et al. (2014) model.

Overall, there are certainly some similarities and differences between the inter-factor correlations in Mirwis (2011), Kaat et al. (2014), and the nine-factor model in this study.

However, it appears that the major differences mostly occur as a result of the five-factor model in Kaat et al. (2014) and the seven-factor model in Mirwis (2011) expanding in this study to nine-factors. Consistent with the expanded model in Mirwis (2011), the nine-factor model correlations are likely lower overall because constructs have been further condensed and items have been distributed across more factors. Comparisons of the inter-factor correlations between Mirwis (2011), Kaat et al. (2014), and the nine-factor model generated in this study, add further evidence that the nine-factor model represents a more complex yet more conceptually clear structure.

Internal consistency reliability estimates were also calculated using both ordinal and Cronbach's alpha. Ordinal alpha estimates ranged from .889 (Oppositionality) to .951 (Irritability/Tantrums) and Cronbach's alpha estimates ranged from .816 (Lethargy) to .931 (Irritability/Tantrums). As mentioned previously, ordinal alpha is the more appropriate statistic when item scales are ordinal and the polychoric correlation matrix is used. The Cronbach's alpha estimates were generated in order to provide a source of comparison with other studies that did not use ordinal alpha. Based on criteria provided by Murphy and Davidshofer (as cited in Sattler, 2008), estimates between .80 and .89 are considered moderately high or good reliability and estimates $\geq$ .90 are considered excellent. Nunnally (1978) suggested that a reliability of .70 is the minimum for research purposes. Thus, internal consistency reliability estimates for scales based on the nine-factor model were generally very strong for research purposes.

Both Mirwis (2011) and Kaat et al. (2014) used Cronbach's alpha coefficients in their studies to estimate internal consistency reliability. Brinkley et al. (2007) did not report any internal consistency reliability estimates. Estimates in Mirwis (2011) ranged from .87 (Lethargy) to .97 (Self-Injurious Behavior). These estimates are relatively similar to the estimates in the

nine-factor model in this study although the Cronbach's alpha estimates in Mirwis (2011) are slightly higher. Estimates in Kaat et al. (2014) ranged from .77 (Inappropriate Speech, in both the calibration and validation samples) to .94 (Hyperactivity/Noncompliance in the calibration sample) and .93 (Hyperactivity/Noncompliance in the validation sample). Once again, these Cronbach alpha estimates are relatively similar to the estimates in the nine-factor model.

Overall, internal consistency estimates in the nine-factor model generated in this study were relatively similar compared to both Mirwis (2011) and Kaat et al. (2014). As such, it appears the decision to embrace a model with a greater number of factors (averaging fewer items per factor) did not substantively attenuate internal consistency reliability estimates. High internal consistency reliability estimates for all factor-based subscales offer further evidence of the psychometric viability of the nine-factor model.

Research question 4 and hypothesis 4. Research question 4 was intended to provide a comparison between the Aman and Singh (2017) five-factor model and the five-factor EFA solution generated (but not selected) in study one. It was hypothesized that the two models would closely match. This was determined by qualitatively comparing factor names from both solutions, contrasting the highest loading items in each factor, and calculating a percentage of overlapping items between the two solutions. Similar factor names were found in Aman and Singh (2017; Irritability, Social Withdrawal, Stereotypic Behavior, Hyperactivity/Noncompliance, and Inappropriate Speech) and in the five-factor model in study one (Self-Injury/Irritability, Social Withdrawal/Noncompliance, Stereotypic Behavior, Inappropriate Speech, and Hyperactivity). The top five highest loading items were similar—though often differing in exact rank across the two different five-factor solutions. A high percentage of items from Aman and Singh (2017) were found in the similar factors in the five-

factor solution in study one. The major difference between the two different models was that the noncompliance-related items in Aman and Singh (2017) appeared to break off from the Hyperactivity factor and connect with the Social Withdrawal factor items in the five-factor solution from study one (named Social Withdrawal/Noncompliance).

Comparing the results from these two factor solutions revealed many similarities between them. In general, the five-factor structure in Aman and Singh (2017) was relatively intact in comparison to the five-factor solution from study one. The Inappropriate Speech and the Stereotypic Behavior factors in both studies contained the same items. This is yet another sign of the robustness of these two factors in the ABC-C. The movement of the noncompliance-related items from the Hyperactivity factor in Aman and Singh (2017) to the Social Withdrawal factor in study one was an interesting change (i.e., Hyperactivity/Noncompliance in Aman and Singh, 2017, and Social Withdrawal/Noncompliance in the five-factor solution from study one); although both factors as constituted are conceptually crowded, each containing items that may allow for further construct or subconstruct distinctions. The Irritability factor in Aman and Singh (2017) was also very similar to the Self-Injury/Irritability factor in the five-factor solution in this study (14 out of 15 items were similar). The major difference between them was that the three self-injury items loaded the highest in the five-factor solution in study one, making it difficult to avoid including self-injury as part of the factor name (considering its most dominant loadings). The first self-injury item in the Irritability factor in Aman and Singh (2017) was the fifth highest loading item in the factor. It thus makes sense that self-injury did not appear as prominent in defining the factor as it does in this and other studies. That said, it is important to point out that self-injury items make up the top two items in the Irritability factor in the five-factor solution in Kaat et al. (2014) and three of its four top items. It is possible that the higher

correlations of the self-injurious behavior items in Kaat et al. (2014) are a result of using an ASD sample in contrast to the ID sample used in the original ABC study (Aman & Singh, 1985a), as persons with ASD have been shown to exhibit higher rates of self-injurious behavior than in individuals with ID (Minshawi et al., 2014).

Overall, comparing the five-factor model in Aman and Singh (2017) and the five-factor solution in study one indicated that the factors and the specific constructs are relatively stable across the two studies. But, the findings of Mirwis (2011) and the present study raise questions as to how consistent factor solutions consisting of more than five factors might be across the samples from different studies. This is a difficult question to answer given that most studies did not look beyond five or six factors. Though the five factors seem to consistently appear across studies, what if more factors were consistently available to not just account for more common variance but also to potentially make more nuanced clinical distinctions? It also raises questions as to whether using an ASD sample could be a key reason for some of the changes in factor loadings or whether the ASD population requires a different factor model to capture its item variation. Thus, the ASD population might require a different factor solution than the one currently used by Aman and Singh (2017) and perhaps a more complex factor model should be examined in other populations as well.

Study One Implications

Theoretical. Perhaps the core theoretical question in study one concerns whether or not the ABC-C requires a different factor structure for use with the ASD population. The three prior factor analytic studies performed with ASD samples resulted in somewhat different outcomes. Brinkley et al. (2007) concluded that the five-factor author version of the ABC-C was robust within the ASD population. However, Brinkley et al. (2007) urged further assessment of the

Irritability scale particularly for the ASD population given the presence of the self-injurious behavior items. Kaat et al. (2014) concluded that the five-factor author version of the ABC-C was robust for the ASD population and Aman and Singh (2017) reiterated this assertion. On the other hand, Mirwis (2011) questioned whether the ASD population does in fact yield a more complex structure after he found seven meaningful factors in his EFA. Results from study one seem to point to three different possibilities with regard to whether or not the factor structure of the ABC-C may differ for individuals with ASD.

The first possibility is that the nine-factor solution chosen in study one provides evidence that the ABC-C requires a different factor structure for individuals with ASD. No prior EFA with the ABC-C with an ASD population had even considered a nine-factor solution. The factors generated from the EFA are all made up of core and associated features of ASD. For example, the Self-Injury/Aggressiveness factor, similar to the Self-Injury factor as found in Mirwis (2011), primarily represents a more common behavior (self-injury) in individuals with ASD than individuals with ID (Soke et al., 2016). Social Withdrawal, which became a standalone factor in the nine-factor solution in study one (which split from the Lethargy construct) is a common trait of individuals with ASD who struggle with social interactions (APA, 2013). (To note, Aman and Singh (2017) dropped the Lethargy factor name from the Lethargy/Social Withdrawal factor in the recent ABC-C2 manual without explanation. Perhaps this highlights the perceived relative importance of the social withdrawal construct of the factor). In sum, there may be certain traits inherent in individuals with ASD that are more pronounced than in individuals with ID, resulting in a different pattern of variation and a need for an ultimately more expansive factor structure than had been found previously in an ID population.

The second possibility is that the nine-factor structure chosen in study one does not provide evidence that the ABC-C requires a different factor structure for individuals with ASD. Aman and Singh (2017) argued that a different factor structure for the ASD population is unnecessary, and that the five-factor structure should suffice as the generalized standard across different populations. However, given that lack of prior exploration of more complex factor structures for the ABC within the ID or other populations, it seems worth considering the possibility that the five-factor model may reflect an under-factored model more generally across populations. It could be that the current five-factor model author version of the ABC-C is simply an under-factored model and that the nine-factor solution is an improvement upon the current structure, which could be generalizable across populations. For instance, it has been argued in this study that certain factors in the five-factor author version (e.g., Irritability, Social Withdrawal) are conceptually crowded. This may be the case for the ASD population, but it could also be true for the ID population as well. Another example can be seen with the one new factor introduced in the nine-factor solution that had not appeared in any other factor solution of the ABC-C: Oppositionality. Researchers have found that the DSM-5 (APA, 2013) model for oppositional defiant behavior applies similarly for ASD and non-ASD populations alike (Mandy, Roughan, & Skuse, 2014). It seems unlikely that this factor would be more distinct in ASD than other clinical populations that vary on this dimension of behavior. Thus, the nine-factor solution should be considered for evaluation as a factor structure for the ABC-C in the ID and ASD populations, and potentially other populations as well.

The third possibility is that it is still unclear as to whether or not there should be a different structure for the ABC-C for the ASD population. Certainly the nine-factor solution seemed to highlight underlying weaknesses in the current five-factor author version of the ABC-

C for the ASD population. For instance, the inter-factor correlations of the nine-factor solution did not reveal any unusually high correlations between factors in the EFA, providing evidence for further latent construct distinctions not recognized in the five-factor solution. But, as mentioned previously, perhaps the current five-factor solution is not the best fitting model of the ABC-C for the ID population as well. It could also still be the case that the nine-factor solution is not the most appropriate solution for the ASD population either, with a better model having not yet been articulated in another study. Nonetheless, potentially calling into question the structure of the five-factor model for the ID population makes it challenging to assess whether a different structure of the ABC-C for the ASD population would be appropriate. As a result, it may be difficult to provide a definitive answer to the core theoretical question in study one alone.

However, gaining clarity as to whether or not there should be a different structure for the ABC-C for the ASD population can ultimately be addressed in future factor analyses. This effort could be furthered by performing multiple EFAs to assess if different populations generate the same or different model solutions. It could also be advanced by performing multiple CFAs and directly assessing the fit of the nine- and five- (and whatever other) factor models with both an ID and ASD population to determine whether outcomes are repeatedly similar among the different populations or whether there is a distinct difference.

Research methodology. With regard to research methodology in study one, there are two essential aspects that need to be highlighted. The first key methodological element involved the decision to use four different factor retention tests. Between three and eleven factors were ultimately considered in study one. This is a much larger range than had been looked at in the three prior factor analyses for the ABC-C with an ASD sample. It is important to note that the large range of factor solutions considered was data-driven and not based on any historical

precedent. As a result of this wide range, a new solution, the nine-factor model, was ultimately selected. It was not expected and was not hypothesized prior to carrying out the EFA—reflecting the truly exploratory nature of the analytic process.

It was argued in this study that the other factor analyses of the ABC-C for the ASD population (and for non-ASD populations) often failed to perform more rigorous and thorough EFAs, particularly focused on the failure to consider a larger range of factor solutions for retention. As a result, these more limited factor solution choices potentially prevented the researchers from exploring alternative, and perhaps more nuanced and appropriate solutions than the ones they were choosing from. Factor analytic studies of the ABC-C with an ASD sample prior to the present study had only considered a four-, five-, or six-factor models, except Mirwis (2011) who considered five-, six-, seven-, and eight-factor models. Both Brinkley et al. (2007) and Kaat et al. (2014) only used a scree test and the Guttman Kaiser Criterion to determine their initial solutions to explore. Brinkley et al. (2007) only looked at a four- and five-factor model and did not report results of their factor retention tests. Kaat et al. (2014) considered four-, five-, and six-factor models in their EFA and reported a scree plot analysis showing a five-factor solution and the Guttman Kaiser Criterion showing 11 factors with eigenvalues > 1. It is unclear why Kaat et al. (2014) did not directly address the results of the Guttman Kaiser Criterion in their study and only focused on the range of solutions surrounding the five-factor scree result. The key point here is the fact that a shortcoming of both Kaat et al. (2014) and Brinkley et al. (2007) in not relying on the more accurate factor retention tests likely biased the factor solutions they were able or willing to consider. The parallel analysis used in Mirwis (2011) ultimately resulted in the consideration and retention of a seven-factor solution. In study one, the inclusion of the MAP test led to the consideration and retention of a nine-factor solution. Thus the core

methodological implication is that the failure to use the more advanced factor analytic retention test methods (parallel analysis and the MAP test) may have negatively biased the previous factor analyses for the ABC-C with an ASD population in terms of the range of solutions explored. Moreover, it is also not out of the question to consider whether the current five-factor author version of the ABC-C (Aman & Singh, 2017) contains fewer interpretable factors than may actually be present in the data for the ID population because more modern and accurate factor analytic retention tests were not used.

The second key methodological element employed in this study involved the use of special education staff members as raters. Two of the previous factor analyses of the ABC-C with an ASD population (Brinkley et al., 2007; Kaat et al., 2014) each used caregivers as raters while only Mirwis (2011) used special education staff members. Mirwis (2011) generated a unique seven-factor model in his study while a nine-factor solution was chosen in study one. Thus, both of the EFA studies that used special education staff as raters retained factor solutions involving more than five factors. This opens up the question of whether there is a quantifiable difference in factor outcomes between the special education staff raters and caregivers as raters.

The Standards for Test Design and Development (SEPT; SEPT, 2014) highlight the idea that validity needs to be established for a scale when it is used in a unique way. Researchers have emphasized that when using a rating scale, different raters and distinctive environments can potentially influence outcomes (Portney & Watkins, 2000; Tziner et al., 2005). Certainly special education staff members have a different perspective than caregivers. They are interacting with subjects in a separate environment than parents and they maintain a different role than parents as well. Special education staff members are also typically interacting with multiple individuals in their environments and thus may appraise the frequency, duration, intensity, and function or

intention of behaviors differently than parents. The fact that Mirwis (2011), and now this study, generated more complex factor solutions using special education staff as raters certainly raises questions as to their potential influence on the overall factor structure. Nonetheless, it is inappropriate to make any strong conclusions about the specific influence of the special education staff members as raters and how any environmental variables might have affected their ratings on the ABC-C as this aspect was not specifically assessed in this study.

Practice. Results from study one potentially have major practical implications for the use of the ABC-C with ASD populations. The viability of the five-factor author version of the ABC-C (Aman & Singh, 2017) can appropriately be called into question given that two factor analyses (Mirwis [2011] and this study) out of the four total of the ABC-C with an ASD population—both of which relied upon more rigorous factor retention methods and processes—have been shown to have a more expansive, interpretable, and nuanced factor structure. A strong argument can be raised that the CFA analysis in study two, which tested the fit of the Mirwis (2010) seven-factor model and the nine-factor model in this study, is the best way to determine whether these viability questions have merit. Yet, as Church and Burke (1994) argue, reproducing a model in EFA across different samples also offers solid evidence of the strength of a model, given that it is generated without any limiting parameters. At this stage the most logical answer is to continue to perform further rigorous EFAs of the ABC-C with ASD samples and see if these more expansive factor models appear—giving a better sense of the impact of sampling variation on the factor structure across samples. But, the question has to be raised where that leaves a researcher who desires to use the scale now that the current author version of the model has been legitimately questioned as a result of this study.

The results in study one also raise doubts as to the practical value of particular factors that appear to be conceptually crowded in the five-factor model. For instance, the Irritability factor in the Aman and Singh (2017) five-factor model maintains multiple items that support an Irritability construct, but it also contains three self-injurious behavior items that may not be directly related to Irritability—or may over-represent self-injury within the irritability context. From a practical standpoint, a behavior intervention may need to target self-injury or irritability or both, yet having a scale that combines the constructs and results in a singular subscale score could make it challenging to appropriately assess intervention progress. Splitting the self-injurious items off from the Irritability factor, as occurred in the nine-factor model and in the Mirwis (2011) seven-factor model, seems to be more advantageous. Similar issues regarding conceptual crowding also arise in the Aman and Singh (2017) five-factor model with regard to the Hyperactivity/Noncompliance factor. Thus, the nine-factor model helped to highlight that these two aforementioned factors in particular in the five-factor model might have diminished value in both research and practice.

Overall, it is fair to ask whether a researcher should continue to use the five-factor author version of the ABC-C with an ASD population now, before further studies are performed, despite the fact that the factor structure and the practical utility of certain factors have been legitimately questioned. It is likely best to leave that question to each individual researcher and have her decide her own level of confidence in the instrument as currently constructed. It should also be pointed out that there are apparent strengths contained in the five-factor model as well, such as with the Inappropriate Speech and Stereotypic Behavior factors. These two constructs have been consistently found across all four factor analyses of the ABC-C with ASD populations. As long as ASD researchers are fully aware of the potential weaknesses of the

overall structure and individual factors in the author version of the five-factor model, they can appropriately judge whether the ABC-C is still suitable for their needs prior to more research being performed on the scale.

Study One Limitations

Despite the many strengths in study one, there are still some important limitations that need to be acknowledged. Using an extant dataset limited certain methodological choices. Having limited resources including budget, time, and people power, also constrained options. The primary limitations in study one involve the sample and the raters, external validity and generalizability, rotation, and extraction criteria.

Sample and raters. There are specific limitations regarding the sample that occurred as a result of using an extant dataset. Certain variables that would have been useful to measure were not accounted for in the dataset. These variables would have provided more clarity as to the nature of the sample and could have influenced or helped contextualize outcomes to some degree.

First, although there was a screening process at the special education agency to obtain an ASD classification and participate in their center-based program, this process did not include the agency performing their own ASD assessments in a majority of cases. As a result, classification of individuals did not necessarily include assessment with a gold-standard instrument such as the ADI-R or the ADOS-2. It would have made for a more rigorous classification process and provided even more confidence in the diagnostic label. Additionally, it would have been helpful to have performed cognitive testing specifically for this study, including using a more limited number of instruments across cases to gain more confidence in the consistency and strength of the DQ metric. Furthermore, although all individuals in the study were participants in special

education classrooms, meaning that they had substantial functional impairments, data on an adaptive assessment measure would have provided more clarity as to the their level of impairment. This is particularly important given that DQ scores in study one range from 12-112, especially for individuals at the highest end of the DQ range. It is a valuable question to pose in future studies to determine to what extent individuals with certain DQ levels or adaptive behavior levels with ASD could influence model structure or subscale scores.

Another weakness in the dataset was the fact that no information was provided on whether individuals had other comorbid conditions. Additionally, no information was provided on which participants were taking particular medications. Each of these variables could also have had an impact on outcomes as well and would have offered more clarity on the nature of the sample.

The use of special education staff members as raters was also a potential weakness. A legitimate argument could be made that different staff members (e.g., teachers, teaching assistants, speech pathologists, behavior technicians, occupational therapists) each constitute a different classification of rater. Ratings by staff position were not specified in the sample. Although it is unlikely to be the case that raters that work together in the same particular environment will have drastically different perspectives, it is still a valid criticism to point out that raters in this group have different educational backgrounds and training, and that each bring a particular lens to their observations. This could also have been useful information to determine whether there was a distinct difference in ratings based upon staff title.

External validity and generalizability. The present study used special education staff members as raters and generated a more expansive factor structure for the ABC-C when used with an ASD sample. Despite the potential implications of these results, it is still premature to

assume that because Mirwis (2011) also found a more expansive factor structure as well when he used special education staff members as raters, that this is enough evidence to definitively generalize these results beyond these two studies. More EFAs performed in a special education context with special education staff members as raters would be needed before being able to confidently assert the robustness of these results with an ASD sample. It would even be more presumptive to assume that the nine-factor model found in this study would generalize for the ABC-C with an ASD sample to all types of raters or environments. Further, it is still premature to assuredly question the ABC-C factor structure of the ABC-C for non-ASD populations as well, particularly because other populations were not assessed in this study.

Rotation. A direct oblimin rotation was used in study one. The other factor analyses for the ABC-C with an ASD sample used similar but slightly different techniques. For instance, Mirwis (2011) used a promax rotation, Brinkley et al. (2007) used both a promax and varimax rotation, and Kaat et al. (2014) used a Crawford-Ferguson quartimax rotation. It is beyond the scope of this study to debate the intricacies of each rotation and how those differences may affect outcomes. However, the fact that each study of the ABC-C with an ASD sample used a different rotation makes it challenging to compare across studies. A limitation in this study could certainly point to the fact that multiple rotation techniques (or extraction techniques for that matter) were not tested to determine whether results would be consistent across methods. This is not to say that all existing methods should have been chosen, but rather, multiple methods could have been tested such that there would be more continuity between studies and more clarity as to whether any particular rotation could substantively impact outcomes.

Extraction criteria. Study one relied upon four different extraction methods: the scree test, the Guttman Kaiser Criterion, parallel analysis, and the MAP test. Only this study used the

MAP test out of the other factor analyses for the ABC-C with an ASD sample. Although using the MAP test can certainly be considered a unique strength of this study, it must also be recognized as a limitation with regard to comparing outcomes of this study to the other existing studies.

The MAP test is considered amongst the most robust modern extraction techniques (e.g., Courtney, 2013; Osborne & Banjanovic, 2016) and in this study it generated a unique solution (the nine-factor model). In contrast, the scree test and the Guttman Kaiser Criterion have their limitations. Courtney (2013) suggested that the scree test is often subjective, such that it tends to work well when factors are strong, but results in poor inter-rater reliability bias when factors are less clear. Fabrigar et al. (1999) argued that the Guttman Kaiser Criterion is not very accurate and has been shown to lead to both over- and under-factoring. Although the results of the MAP test were not accepted blindly, as theory and clinical meaningfulness guided the final decision making, a great deal of weight was provided to the MAP test (and parallel analysis) to help justify decision making. Thus, the limitation in this study is not any direct problem with the use of the MAP test, rather, because the MAP test is unique to this study its outcomes cannot be directly compared to any of the other existing studies. Because these other studies did not use the MAP test nor the parallel analysis (except for Mirwis [2011]), it makes it challenging to determine whether the chosen factor structure in this study is truly unique and the result of something inherently different in this sample or whether it is the result of the other studies' failures to use this more advanced technique.

Study One Future Research Implications

Results from study one open up multiple avenues for future research of the ABC-C with the ASD population. These future studies could improve upon some of the weaknesses in study

one and build upon the results generated herein. They could also assess the strength of outcomes found in this and previous studies and move the literature forward to gain more clarity as to the application of the ABC-C with an ASD population.

First, with regard to improving upon this study, future studies should collect certain key information about the sample and the raters if possible. Because ASD is a spectrum disorder, and there are varying presentations of ASD, it is important to be able to determine in future studies which variables may have a certain degree of influence on the factor structure or even on factor scores. This should include IQ and adaptive behavior information because both are key in determining the level of functioning of individuals with ASD. It is likely not enough to cite IQ as a proxy for needed level of support. Additionally, further information regarding co-morbid disorders, medication usage, and functional language skills would help to identify if these variables maintained any particular influence on outcomes. Only Kaat et al. (2014) assessed the impact of multiple demographic variables (e.g., age, sex, IQ, adaptive behavior, and language), and they did find moderate to small effects in subscale scores. Information should also be gathered on raters, particularly if a study is done with special education staff to determine whether raters in a certain role (e.g., as teachers or speech therapists) show rating differences that may impact the factor structure.

Second, with regard to improving upon this study, different rotations and extractions should be performed in any future study in order to determine whether there is a distinct difference in outcomes when these varying methods are used. Because each of the different studies with the ABC-C with an ASD sample were not uniform in their rotation (and extraction) methods, it creates another variable that needs to be addressed in order to have greater confidence in the ultimate solution. This is not to say that methods should be used if they are

inappropriate (e.g., if data is found to be non-normal it is not necessary to use a technique that is appropriate only for normative data) but, for example, researchers could test both a promax and direct oblimin rotation with their datasets to assess for any particular influence. In the same vein, future studies should also use the same factor retention tests, particularly parallel analysis and the MAP test, in order to ensure that the most powerful modern tests are used to help determine the most interpretable solutions.

With regard to moving the literature forward in future studies, more EFAs should be performed of the ABC-C with an ASD sample. First, this study, although not perfect, represents a thorough and robust factor analysis that is key to determining the best fitting model in a future CFA. One of the weaknesses of the existing literature for the ABC-C with an ASD sample is the fact that there are so few factor models to assess and there are various questions regarding the thoroughness of the exploratory methods that were used. More robust EFAs of the ABC-C with the ASD population would solve this issue. In addition, as Church and Burke (1994) imply, more robust EFAs would also help to establish whether a particular model or construct is appearing on a consistent basis (e.g., a self-injurious behavior or oppositional behavior factor), which would provide greater evidence for the strength of certain factors and models. Second, more EFAs need to be performed to determine the influence of the different raters on the ABC-C with an ASD sample. This study and Mirwis (2011) relied upon the same type of raters while Brinkley et al. (2007) and Kaat et al. (2014) relied upon caregivers. Future studies, if possible, might obtain multiple ratings from both caregivers and special education staff to determine if there is a difference in outcomes.

Another way to move the existing literature forward would be perform further validation assessments to test the strength of the different factors found in this study. For instance, a

concurrent validity assessment would help to assess how well factor constructs derived in this study align with similar factor constructs from other scales. This would be particularly important for the two newly independent factors generated in the nine-factor model: Noncompliance and Oppositionality. Concurrent evidence, especially both convergent and divergent, would help bolster the legitimacy of these two factors.

One of the outcomes of the nine-factor solution in this study involved a more expanded factor model rather than maintaining more conceptually crowded factors as occurs in the five-factor author version of the ABC-C (Aman & Singh, 2017). In particular, the Irritability factor in Aman and Singh (2017), which was broken up into more than one factor in the nine-factor model, deserves more intense scrutiny. The self-injurious behavior items were also broken off from the Irritability factor and given their own factor in Mirwis (2011). This factor has been used as a primary outcome measure in various consequential psychopharmacological-based studies, such as the study by McCracken et al. (2002), which was one of the main studies that led to FDA approval of Risperidone in children with ASD. Thus, it would be interesting to assess the influence of the self-injurious behavior items in these Irritability factor scores. Additionally as Bolte and Diehl (2013) found, the ABC-C was the most used measure for assessing hyperactivity symptomology across ASD intervention studies where hyperactivity was measured as an outcome. In the nine-factor model, both Hyperactivity and Noncompliance maintained their own independent factors. In the Aman and Singh (2017) version of the ABC-C these constructs are combined in a singular factor. As with the Irritability factor, it would be interesting to determine the influence of Noncompliance items on the overall subscale scores in each of these studies that used the Hyperactivity/Noncompliance factor as an outcome measure.

Finally, Mirwis (2011) suggested that inter-rater reliability, test-retest reliability, and treatment sensitivity of the ABC-C should be performed to further assess its usability with the ASD population. This study did not assess these key elements, as only factor structure and internal consistency reliability estimates were examined. It would be useful for future studies to determine whether the ABC-C for the ASD population demonstrates adequate inter-rater and test-retest reliability as well. In addition it would be useful to determine whether reliability statistics hold up in a variety of other clinical contexts, or if a particular hypothesized model (e.g., the nine-factor model) is truly specific to only the ASD population.

Summary and Interpretation of Findings for Study Two

Research question 5 and hypotheses 5a and 5b. Research question 5 was focused on a) evaluating the absolute and relative fit of the nine-factor ABC-C model derived from a sample of individuals with ASD, rated by special education staff members, and then b) comparing the fit of that model to that of the existing models of the ABC-C found in ASD samples (or proposed for use with individuals with ASD). A confirmatory factor analysis (CFA) was performed using a weighted least squares mean and variance adjusted (WLSMV) approach to generate five fit indices (χ^2, SRMR, RMSEA, CFI, TLI) for evaluation of the individual models. A maximum likelihood estimator was also used to generate two other fit indices (AIC, BIC), which enabled a direct comparison of several of the different ABC-C models for the ASD population. Results from the CFA revealed the nine-factor ABC-C model from study one meeting or approximating cut off-values on four different fit indices (SRMR, RMSEA, CFI, TLI). As a result, hypothesis 5a was supported as the nine-factor model was shown to adequately fit the ABC-C variance-covariance matrix of the second sample. Results from the AIC and BIC fit tests revealed the nine-factor model to be the best fitting model compared to the four- and five-factor models from

Brinkley et al. (2007), the five-factor model from Aman et al. (1985a), and the seven-factor model from Mirwis (2011). In addition to the AIC and BIC indices, the nine-factor model distinguished itself across four of the other fit indices (SRMR, RMSEA, CFI, TLI) compared to the other five tested models—which included the Sansone et al. [2012] model for a Fragile X population. (However, these other fit indices are not generally used for cross-model comparisons.) Only the adjusted χ^2 statistic maintained relative parity ($p < .001$) across all six tested models. Thus, hypothesis 5b was supported as results from the AIC and BIC fit indices provided evidence that the nine-factor model demonstrated a better fit to the second ASD sample ABC-C variance-covariance matrix than the previous ABC-C factor models for the ASD population. In addition, results from the inter-factor correlation outputs revealed moderate to high correlations among multiple factors.

It is important to note that although the nine-factor model consistently generated more robust fit statistics than the other models that were tested, it does not mean that the nine-factor model is objectively the *best* model. The six models tested were fit to one particular ASD sample ABC-C variance-covariance matrix with ratings obtained by special education staff members. Only the AIC and BIC fit indices used in study two enabled a more direct comparison between models, based on the unique variance covariance matrix used only in study two. Therefore, although the nine-factor model outperformed the other tested models across six of the seven fit indices, it would be inappropriate to simply objectively generalize the results without taking the characteristics of the unique validation sample into account.

It is precisely the nature of ASD that makes the validation sample used in this study truly unique as well. Masi, DeMayo, Flozier, and Guastella (2017) highlighted the heterogeneity in the spectrum of presentations found in ASD. They discussed the continuing disagreements

regarding the number of potential different diagnoses under the umbrella of ASD, the influence of cognitive impairments on presentation, and the range of adaptive and cognitive skills found in individuals with the disorder. In addition, Masi et al. (2017) underscored the fact that even culture has biased the development of the diagnostic criteria of ASD, with Western cultural participants having the largest influence. For instance, Masi et al. (2017) illustrated that in certain Asian cultures, a lack of eye contact, a common feature in individuals with ASD, is often not viewed as highly unusual in a culture that regards eye contact with older people or authority figures as disrespectful. Thus, using a particular sample of individuals with ASD in a study and attempting to generalize the sample to the larger population of individuals with ASD can be problematic given the fact that samples can vary greatly in their presentations or expected behaviors. Even the sample in study two highlights some of this spectrum with regard to cognitive skills, with participant DQ scores ranging from 12 to123. Further, as Masi et al. (2017) argue, without particular biological markers distinguishing between presentations of individuals with ASD, the need to rely completely on behavior to assess and treat individuals with ASD is highly challenging. Therefore, although the nine-factor model appeared to distinguish itself in study two, it is certainly conceivable that outcomes could potentially vary greatly with a different ASD sample.

However, results from study two seemed to generally reflect previous results from the two CFAs (i.e., Brinkley et al., 2007; Kaat et al., 2014) of the ABC-C with ASD samples. Kaat et al. (2014) examined the five-factor Aman et al. (1985a) model, the four- and five-factor Brinkley et al. (2007) models, and the Sansone et al. (2012) model. Satorra-Bentler χ^2 values in the Kaat et al. (2014) CFA were significant for all models, as were the χ^2 values for all models in study two. RMSEA values were slightly higher in Kaat et al. (2014) ranging across the four

aforementioned models between .081 and .086, compared to .071 to .089 in study two. SRMR values were similar across the four models tested in Kaat et al. (2014) ranging from .09 to .10, compared to .093 to .116 in study two. Brinkley et al. (2007) only assessed their own five-factor model generated from their study in their CFA and included two of the fit indices used in study two: the Normed Fit Index (NFI, also known as the TLI), and the RMSEA. The RMSEA value in Brinkley et al. (2007) was .091 compared to .078 in study two—a slightly better though still elevated value. The NFI in Brinkley et al. (2007) was .89 compared to a TLI of .902 in study two, both relatively similar obtained values. Overall, consistency of results replicated across three total CFA studies of the ABC-C with an ASD sample provide further evidence of the weakness of the existing ABC-C models in the ASD population.

There are two key differences between the previous CFAs with the ABC-C and the CFA from study two. The first is that one model, the nine-factor model, distinguished itself across the various fit indices. In Kaat et al. (2014) there was relative parity across the different models tested. This included the validation sample, which was split up into subsamples to isolate certain outcomes for age (> 6 years vs. < 6 years), IQ score (> 70 vs. < 70), and level of adaptive behavior supports. In Kaat et al. (2014) only one model stood out as the poorest fitting model (Brown et al., 2002), although it was not from an ASD sample. Had Kaat et al. (2014) relied upon a greater number of fit index tests, as was done in study two, a certain model potentially could have more clearly emerged as a better fitting model. In addition, the omission in Kaat et al. (2014) of indices that would have enabled a direct comparison of models (e.g., AIC and BIC, as were used in study two) prevented the authors from making more substantial evidence-based decisions to justify their ultimate selection of the five-factor model over the other tested models. Overall, perhaps the most obvious implication of the nine-factor model distinguishing itself in

study two is that it now has confirmatory evidence supporting it as a potentially viable model for the ABC-C in the ASD population.

The other major difference between the CFA in Kaat et al. (2014) and the CFA in study two was the inclusion of the Mirwis (2011) seven-factor model in study two, which was not assessed in Kaat et al. (2014). The seven-factor model did not distinguish itself in study two across the different fit indices compared to the other tested models, although it did produce the second lowest AIC and BIC scores compared to the nine-factor model. That said, Mirwis (2011) was one of the three studies of the ABC-C with an ASD sample, and it was important to assess the viability of the seven-factor ABC-C model given that so few hypothesized ABC-C models existed for the ASD population. It was also the only study of the three existing studies of the ABC-C with an ASD sample prior to study two to use special education staff members as raters. Including the model by Mirwis (2011) in the CFA in study two enabled two models (Mirwis [2011], and the nine-factor model from study one) derived from special education staff member ratings to be examined alongside four models (Sansone et al. [2012], the two models from Brinkley et al. [2007], and Kaat et al. [2014]) generated with parents as raters. Although the rater variable was not specifically examined in this study, distinctions between the differently rated models should certainly open up questions regarding the potential impact of rater type on outcomes. As such, because there was a noticeable difference between the nine-factor model and the other assessed models, there are clearly questions worthy of future exploration regarding the possible influence of rater type.

Study Two Implications

Theoretical. The core purpose of study two was to assess the viability of the nine-factor model of the ABC-C for the ASD population, generated in study one, alongside the other

existing hypothesized models. Results from the CFA confirmed the nine-factor model to be a reasonable fitting model, and one that fit the ASD validation sample ABC-C variance-covariance matrix better than the previous ABC-C factor models for the ASD population. The most important theoretical implication here is the possibility that the nine-factor model is a closer approximation to a "true" ABC-C measurement model for the ASD population. (Though it is theoretically possible for many models to fit the same data equally well, the models tested in the present study are the only current conceptually defensible models. Still, in theory there is no way to know a "true" latent model with certainty.) However, it is too early to generalize these results at this stage as additional EFAs and CFAs are needed across multiple samples and under a variety of conditions before having enough evidence to make such a claim.

All that said, results from the CFA in study two provide some additional information for discussing the differentiation between the three possible theoretical implications raised at the end of in study one: a) the ABC-C for the ASD population requires a different factor structure than for the ID population, b) the ABC-C does not require a different model for the ASD population, or c) is still unclear whether a different model is necessary for the ASD population. The CFA analysis provided evidence that the nine-factor model distinguished itself compared to the other existing models when fitted to a variance-covariance matrix consisting of data derived from individuals with ASD. These results could be providing an indication that there is something inherently different about the ASD population that necessitates a different theoretical model than the typical ID population. However, the results also raise questions as to whether the nine-factor model is viable across all different populations, and in particular that the nine-factor model, or something like it, might be the most useful with an ID population as well. The final implication, that the results of the CFA have not changed the situation and that it is still unclear whether a

different model is necessary for the ASD population, is perhaps the most vexing supposition at this point.

As highlighted in Masi et al. (2017), caution must be maintained with regard to generalizing results of studies with individuals with ASD as a result of the heterogeneity inherent in this population. Further, the nine-factor model in study two expanded upon the structure of the existing five-factor model of the ABC-C (Aman & Singh, 2017), but did not necessarily result in a structure that clearly highlighted more features in an ASD population as opposed to an ID population. Factors in the nine-factor model such as Self-Injury/Aggressiveness, not found in the Aman and Singh (2017) five-factor model, represent some behaviors (e.g., self-injury) that are more common in individuals with ASD than in individuals with ID (Soke et al., 2016). At the same time, factors such as Oppositionality in the nine-factor model and not in the five-factor author version of the ABC-C (Aman & Singh, 2017) appear to be behaviors that are consistent across ASD and non-ASD populations alike (Mandy et al., 2014). It is thus fair to maintain skepticism as to whether the results of study two are conveying something specific about an ASD population as opposed to an ID population, or whether the nine-factor structure is unique to this sample only, or if the original five-factor ABC-C model reflected a generalizable but insufficiently factored model.

Thus, it is appropriate to ask the question as to how much weight should be placed on the results from study two. The most measured answer is to consider these results tentative and provide them the minimum amount of possible weight pending replication because study two is the only existing study to test a nine-factor model and the only study that produced its particular outcomes. The CFA performed in Kaat et al. (2014) did not result in any positively distinct model difference between tested models, and Brinkley et al. (2007) only tested a single model.

Perhaps additional CFAs would enable one to provide increasing weight to the results of study two—under the assumption that the results were repeatedly replicated. In addition, results from study two did not show the nine-factor model or any other model to be an exceptionally fitting model, which certainly points to potential challenges with the model solution, the individual items, or the collection of items. As such, while the results in study two are distinct for the nine-factor model, it is likely most judicious to maintain a neutral position at this point and concede that it is unclear as to whether there is a different factor structure for the ABC-C for the ASD population. That said, results of the CFA certainly warrant one to yet again further question the viability of the author version (Aman & Singh, 2017) of the five-factor model for the ASD population.

It is also important to highlight the fact that the various moderate to high inter-factor correlations potentially represent the presence of higher order or overlapping factors. Inter-factor correlation results from the CFA cannot be ignored given the high correlations between some factors. There could be other explanations for these correlations (see Study Two Limitations), but it is possible that there are higher order or overlapping factors present. In particular, the highest correlations between factors are the most worthwhile targets to address, such as between the Noncompliance factor and the Lethargy factor (r = .848), and the Oppositionality factor and the Irritability/Tantrums factor (r = .874). There is also a possible implication that the smaller factor models (e.g., the Aman et al. [1985a] five-factor model) with certain factors with large numbers of indicators that appear to be conceptually crowded (e.g., Irritability) could in fact be functioning almost as a composite of lower-order latent factors rather than as a single, indivisible factor or construct. Thus, the potential presence of higher-order factors should be assessed in any future studies.

Research methodology. There were three main implications regarding the research methodology for study two, two of which are extensions of implications from study one. One of the core arguments presented in study one involved the need for an EFA to be performed on the ABC-C in an ASD sample using a more thorough and rigorous factor exploration and retention process. The thorough factor retention process used in study one led to the consideration of a wider range of factor solutions than had been examined in previous studies and ultimately resulted in the selection of a nine-factor solution. The main point of this argument was that the failure to use the more advanced factor retention test methods in previous EFAs for the ABC-C in ASD samples could have resulted in an inadvertently limited selection of factor solution options, leading to potential suboptimal final factor solutions. The contention then was that the nine-factor solution that resulted from the EFA process in study one would be shown to be a better fitting model compared to the previous factor solutions for the ABC-C for an ASD sample. Results from the CFA in study two revealed evidence that the nine-factor model was the better fitting model on the sample ABC-C variance-covariance matrix when compared to the previous ABC-C factor models in the ASD population (i.e., when directly compared using AIC and BIC fit indices). It also resulted in outcomes either approximating or meeting fit index cut off values for model acceptability across multiple indices, unlike the other models tested. The implication then is that future EFAs for the ABC-C need to use similar rigorous processes in order to generate the most robust hypothesized models. As a result of the failure to use these processes in previous factor analyses of the ABC-C, highlighted by the results in study one and now study two, multiple questions should be legitimately raised regarding the viability of the current factor structure of the author version of the scale in the ASD population (Aman and Singh, 2017) and in other populations as well.

The second major implication from study one that is also relevant to study two involves the use of special education staff members as raters. Simply, the results from the CFA, using a validation sample of special education staff members, did not dispel previous questions from study one about the potential influence of rater type on outcomes. The nine-factor model, derived from an EFA made up of ratings by special education staff members, maintained the most acceptable fit statistics across the different models tested on the special education staff member-rated validation sample. Thus, it is legitimate to question whether the results would differ when assessed using ratings completed by parents.

The third implication of the CFA methodology in study two involved the appearance of variables with slightly negative residual variances (item 34, *cries over minor annoyances and hurts*, in the Brinkley et al [2007] four- and five-factor models and item 46, *repeats a word or phrase over and over*, in all of the other models tested). The factor loadings for these items were subsequently fixed to a value of 1 in order to properly run the estimation analysis. As noted previously, fixing the factor loading of item 34 had a negative impact on the fit indices in the four- and five-factor models in Brinkley et al. (2007), though it was not substantive enough that it greatly altered the assessment of the models' viability. Fixing the factor loading of item 46 did not have any impact on the fit indices across the other models. Residual variances in item 34 and item 46 revealed issues with multicollinearity, meaning that items that are highly correlated with other items in the model can result in difficulties in estimating model fit. For instance item 46 is similar to item 22, *repetitive speech*, in the Inappropriate Speech factor. Item 34, is similar to item 41, *cries and screams inappropriately*. The implication for the multicollinearity in this study is that these two particular items that resulted in negative residual variances likely should be revised or even potentially removed from the model given the issues that they generated.

When models were rerun with these items removed, no substantive differences in model fit were found.

Practice. Results from study two did not necessarily change any of the practice implications articulated at the end of study one regarding whether or not a researcher should continue to use the five-factor author version of the ABC-C (Aman & Singh, 2017) in an ASD sample. However, results from study two add further weight to the argument that the five-factor model is potentially not the most suitable for use with the ASD population. In addition, the issues that arose with multicollinearity and the presence of various crossloadings further suggest the need for scale revision and should give one pause as to whether the current version of the scale is functioning optimally. In fairness however, no scale is ever perfect and all instruments should be continually scrutinized and revised for maximum effectiveness, as is highlighted in the *Standards for Educational and Psychological Testing (SEPT; 2014)*.

It is important to point out that the ABC-C was not designed as an instrument for use in a clinical context with regard to screening or decision-making. It was originally designed to assess the effects of psychoactive drug intervention on aberrant behaviors in individuals with ID living in residential environments (Aman & Singh, 1986). Strictly speaking, it has not been standardized using a large representative normative sample. (In the ABC-C2 manual, Aman and Singh [2017] conceded that the sample norms provided are not actually "normative" [p. 47].) Clinical reference samples cited in the manual (e.g., children and adolescents with ID, children and adolescents with ASD) are not necessarily representative of the larger clinical populations involved. In addition Aman and Singh (2017) stated that they "cannot fully support . . . with research data" the designated clinically significant cutoff scores for the ABC-C, which are at the 80th percentile across "most subscales" (p. 47, Aman & Singh, 2017).

All that said, the expanded nine-factor subscale structure (or similar future expanded structure) could potentially enable more clinically meaningful distinctions to be made (compared to the existing five-factor author version of the scale) if the scale was standardized for clinical purposes. Having an instrument that could assess multiple associated and core behaviors within ASD (e.g., social withdrawal, stereotypic behavior, noncompliance, oppositional behavior, hyperactivity), ID, or other developmental disabilities, could potentially offer clinicians the opportunity to assess outcomes within an applied intervention context. It would fill the current gap in this area (i.e., the lack of currently established measures for intervention with an ASD-population) as highlighted by Bolte and Diehl (2013). It would provide clinicians an appropriate measure that could potentially be sensitive to short-term treatment effects rather than them having to rely upon inappropriate diagnostic measures not designed for that purpose. However, the current lack of clarity concerning the most appropriate factor structure—particularly with regard to ID and ASD—and the lack of adequate norming (such as accounting for the general population or more representative ASD or ID populations, multiple developmental disability populations, etc.) suggest it is presently too underdeveloped to recommend for clinical use in applied, non-research settings.

Study Two Limitations

It is important to acknowledge that study two contained some key limitations. These limitations included aspects of the sample, the generalizability of the results, the analyses that were performed, and the measurement methods that were chosen. Although it is unlikely that the core conclusions of this study are critically threatened as a result of these limitations, they must still be recognized as legitimate vulnerabilities in this study worthy of criticism.

Sample size and potential moderators. A sample size of 243 participants in the validation sample in study two was likely adequate for the analyses that were performed. However, a larger sample size would have been more ideal to further ensure stability and reduce potential bias with regard to estimates and standard errors. As Harrington (2009) explained, there are various expert opinions on sample size requirements for CFA, but in general, the more participants in a sample the better. Further, in this study, the main limitation with regard to having a moderate-sized sample was that potential moderating variables could not be explored. This was not a primary goal of this study nor was it deemed fully necessary at this stage of the factor analytic process. In fact, as mentioned in the limitations section in study one, not all variables of potential interest (e.g., adaptive behavior scores) were available in the extant dataset. However, given the results of study two, which confirmed the potential viability of the nine-factor solution for the ABC-C in an ASD sample, it could have been useful to have had the means to determine whether certain demographic variables (e.g., DQ score or age) had any sizable impact on study outcomes. A larger sample size would have been necessary in order to isolate and measure the potential impact of these variables, as was done with the large validation sample in Kaat et al (2014) with 763 participants. This is not to say that particular suspicions regarding any moderating variables had arisen in study two. However, Kaat et al. (2014) did find small effects on the means for certain variables, but did not find evidence that any particular variables greatly influenced model fit. Given that the make up of the validation sample in study two was considerably different than the sample in Kaat et al. (2014), meaning, for example, that mean age was higher (10.79 years vs. 6.7 years in Kaat et al. [2014]) and percentages of individuals with IQ/DQ < 70 were also much higher (78.1% vs. 47.4% in Kaat et al. [2014]), it would have been informative to have had the ability to assess the potential effects of these

demographics. This is particularly important with an ASD sample, given the heterogeneity of this unique population (Masi et al., 2017).

Generalizability. With regard to generalizability for the results in study two, there are two main limitations. First, given the nature of CFA, generalizing model results is somewhat limited. Across the seven different fit tests used in study two, only two of them (the AIC and BIC) enabled a direct comparison between models, though tests of significance for those comparisons were not possible (i.e., no standard error of the difference available for AIC or BIC). This means that although the nine-factor model was found to have the best AIC and BIC outcomes, this is accomplished more descriptively and not through significance testing. Additionally, the other five fit indices did not allow for direct comparisons. As such, all models were assessed not in direct relation to each other but rather in relation to each model's particular fit with regard to the variance-covariance matrix of the validation sample. As mentioned prior, this is especially true with regard to the heterogeneity inherent in the ASD population (Masi et al., 2017). This means that it is not appropriate, in terms of these fit indices, to declare a model as being a better fit than another model—but rather a better or worse fit to the variance-covariance matrix of the validation sample. This is why more CFAs made up of different samples (and perhaps different raters as well) could result in dissimilar outcomes.

The other major implication with regard to generalizability involves the actual fit statistics of the nine-factor model. As stated previously, the nine-factor model either approximated or met cut off values for all assessed fit indices except for the χ^2. This means that the nine-factor model CFA results showed an adequately fitting model, but not one that comfortably surpassed fit index cut off values. Results from study two must not be over-sold, but rather, the nine-factor model's viability should be based upon the strength of the outcome

data and the theory underlying the makeup of the scale. As mentioned prior, the theoretical underpinnings of the nine-factor model are consistent with behaviors found in the ASD population, but it is still unclear whether the model is especially unique to ASD or more generalizable. This certainly limits the extent to which these results can and should be generalized to ASD or other populations, and potentially points to a need for the instrument to undergo an appropriate modification to improve its theoretical clarity and robustness. The nine-factor model indeed distinguished itself with regard to the other models in this CFA, but that does not mean that its viability is absolute. More EFAs and CFAs would need to be performed in order to gain more confidence in the existing model's overall acceptability.

Measurement and analyses. There are three significant limitations to highlight regarding the measurement and analyses used in study two. First, in the CFA in study two, factor models were specified to freely estimate factor loadings and inter-factor correlations. Any crossloadings of items that appear in EFA (i.e., items that load on more than one factor) were not modeled within the CFA. Each item was assumed to be primarily an indicator of or influenced by one factor. Thus, any minimal or more substantial crossloadings were not accounted for in the CFA. As a result, fit indices for all models were likely negatively affected, although not likely to any substantial degree that would have changed the relative standing of model acceptability. That said, fit index outcomes that were closely approaching cut off scores could have potentially reached those thresholds if crossloadings were modeled.

Second, as mentioned previously, the need to alter the factor loading to one with a residual variance of 0 for item 46 in the Aman et al. (1985a) model, the Mirwis (2011) model, the nine-factor model from study one, and the Sansone et al. (2012) model as well as for item 34 in the four- and five-factor models from Brinkley et al. (2007) highlighted a weakness in the

underlying structure of the EFA model with regard to issues of multicollinearity. Compounded by issues of crossloadings, it is likely that any particular future hypothesized model of the ABC-C will be negatively affected with regard to overall model fit as well. The very existence of some higher crossloading items and issues with multicollinearity likely reflect weaknesses in the overall item set of the ABC-C. A more traditional scale development process would either result in discarding these problematic items or revising them so that the issues would no longer appear. However, neither instrument modifications nor model modifications occurred in this study. As such, fit index outcomes were limited to the conditions of the existing unmodified instrument and existing unmodified models. These limitations were of course self-imposed, as nothing specifically prevented a more exploratory model modification process. In general, as these model flaws make clear, revisions to the ABC-C for the ASD population (and potentially other populations) are likely necessary if the longer-term goal is to improve scale utility and fit to an underlying theoretically defensible model.

Third, as mentioned previously the resulting multiple elevated inter-factor correlations that arose in the CFA of the nine-factor model could suggest the possible presence of higher-order factors or potentially redundant factors. Though factor redundancy was generally ruled out, one major limitation in this study is the fact that the presence of possible higher-order factors was not further assessed. The inter-factor correlations found in the EFA of the nine-factor model certainly did not approach the same high correlation levels. However, Li (2016) reported that the use of the WLSMV estimator in a CFA can result in over-estimated inter-factor correlation levels. The WLSMV estimator was specifically chosen for study two given the nature of the ordinal, non-normal data, but it is possible that inflated, inter-factor correlations were a negative tradeoff. Additionally, Schmitt and Sass (2011) pointed out that crossloadings

are often not modeled in CFA—and were not modeled in the CFA in study two. Schmitt and Sass (2011) argued that because crossloadings are typically accounted for in EFA and different EFA rotations can influence the absolute value of inter-factor correlations (and there is no rotation in CFA) there is often a resulting discrepancy between the inter-factor correlations found through EFA and CFA. Regardless, the presence of these high correlations must raise questions about a possible higher-order structure that if modeled properly could potentially improve the fit of the nine-factor model.

Study Two Future Research Implications

Results from study two open up various avenues that researchers could potentially pursue in future studies of the ABC-C involving the ASD population. These studies could involve moving the existing literature forward by building on the current findings in order to determine whether the nine-factor model or another model is the most theoretically, practically, and quantifiably satisfactory model. Other studies could involve taking a few steps backwards, and adopting a more exploratory focus for the purposes of scale revision. Overall, there are five key future research directions that could be pursued.

First, additional CFAs of the ABC-C with ASD and non-ASD samples are warranted. The results in study two confirmed the potential viability of the nine-factor model for individuals with ASD. However, this is the first study to not only introduce a nine-factor model but also test it for quality of model fit. More studies need to be performed with various ASD validation samples, including those where data were derived from different types of raters (e.g., examining factorial invariance across rater types). One of the more complicated aspects of individuals with ASD is the fact that the disorder is characterized by heterogeneous presentations. This means that samples of individuals with ASD could vary greatly as ASD characteristics and behaviors

can range across a broad spectrum of frequency, intensity, expression, and type. Thus, the need for more CFAs with multiple samples is necessary in order to ensure that this heterogeneity in presentation is adequately represented by different validation samples. Additionally, it would be appropriate to perform more CFAs with non-ASD samples (e.g., the ID population) in order to assess whether the model is robust across non-ASD populations (e.g., examining factorial invariance across sample types) and different rater types as well.

Second, it is important to further address the issue of the elevated inter-factor correlations that resulted from the CFA of the nine-factor model. Analyses need to be performed to determine whether theoretically defensible higher order factors may be present in the nine-factor model and whether the factors as constituted reflect any redundant constructs. Performing concurrent validity analyses with external scales that reflect theoretically similar and dissimilar factor constructs (i.e., evidence of both convergent and divergent validity) would also be useful to determine whether factors as constituted are sufficiently unique and robust.

Third, future CFA studies should assess the influence of potential sample characteristics on scale factor structure (e.g., age, DQ, adaptive behavior, rater type, functional language skills, etc.). Similar to the analyses performed in Kaat et al. (2014), evaluating these sample characteristics would be useful in any future CFAs to determine the potential influence of these variables in relation to the nine-factor model or other factor models of the ABC-C with an ASD (or even a non-ASD sample). It can be argued that this type of analysis is particularly important for the ASD population given the aforementioned range of characteristics (i.e., heterogeneity) of individuals with ASD. To appropriately examine such demographic aspects, sufficiently large samples would be required to allow for the generation of adequately large subsamples to examine the consistency in factor structure across the range of such characteristics.

Fourth, given that the ABC-C was originally proposed for assessing those with ID, but now being used extensively with those with ASD (with or without co-morbid ID), a particularly informative study would examine similarities and potential differences in factor structures across an ID without ASD sample, an ASD with co-morbid ID sample, and an ASD sample of individuals requiring less intensive levels of support. If possible, such a large study could take rater type into account as well (e.g., parent/caregiver vs. special education staff). Such a study could involve assessing for factorial invariance across the different sample and rater types. Such a large study could be more feasibly conducted, if necessary, as a series of studies involving the comparison of various sample types within rater type, and the comparison of various rater types within sample type.

Fifth, there is a clear need for scale revision of the ABC-C. Despite finding a substantive difference in fit favoring the nine-factor model over others, the CFA in study two revealed problems in the item set of the ABC-C indicative of the need for instrument revision. In particular, issues regarding high crossloadings, multicollinearity, and redundancy provided evidence of significant issues with multiple items in the ABC-C. Scale revision could include both eliminating and adding items to factors/subscales for purposes of improving construct validity, distinctness, robustness, reliability, and refining existing language to clarify item meaning or intent. Study two did not include any model modification goals, as these undertakings are exploratory rather than confirmatory in nature.

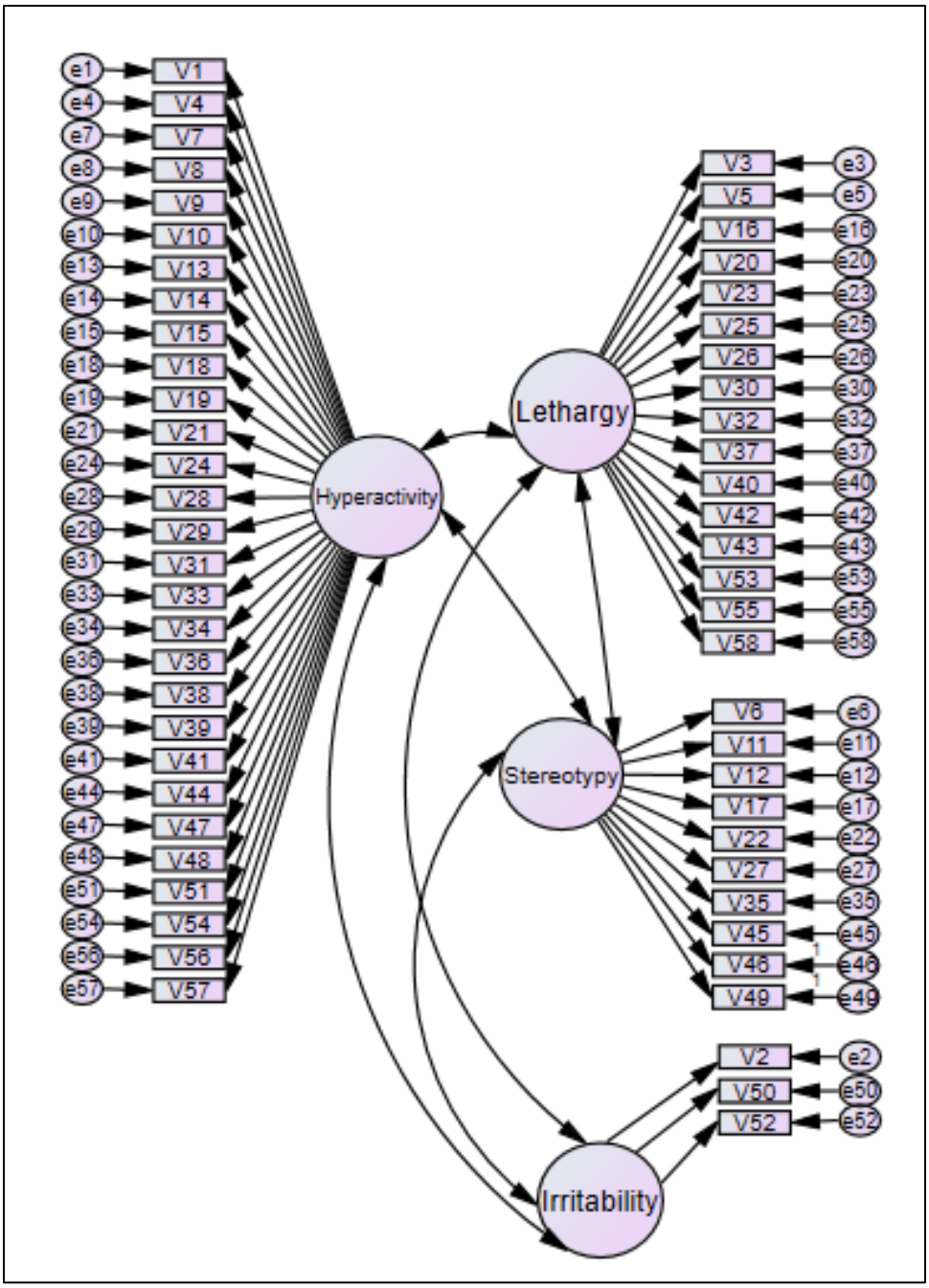
It can be argued that performing multiple EFAs and CFAs of the ABC-C in the hopes of finding the most acceptable version of the model may ultimately be an undertaking with limited potential for greater improvement unless the core foundation of the scale, its items, are optimized such that they are designed to be as effective as possible. This would include isolating

theoretical constructs that can be used in a research or clinical setting that would enable a researcher the ability to more effectively target particular behaviors. These constructs should be theoretically clear and either intentionally limited to a particular population (e.g., ID or ASD) or intentionally designed with generalizability across populations in mind. It can be legitimately argued, at this time, that scale revision should be the highest priority with regard to future psychometric work on the ABC-C.

APPENDICES

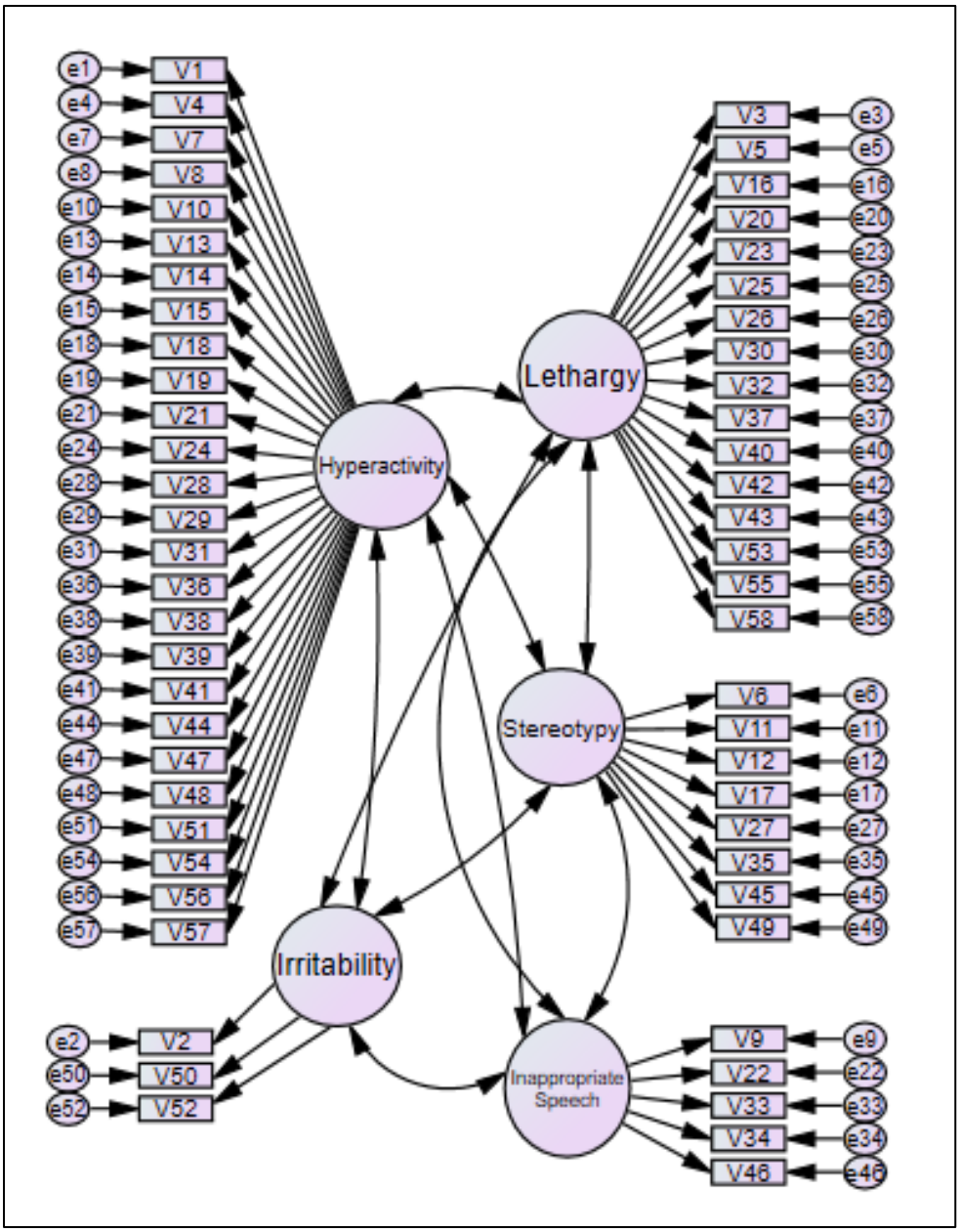
APPENDIX A: EFA Model 1

Figure 15. *Brinkley et al. (2007) four-factor model*



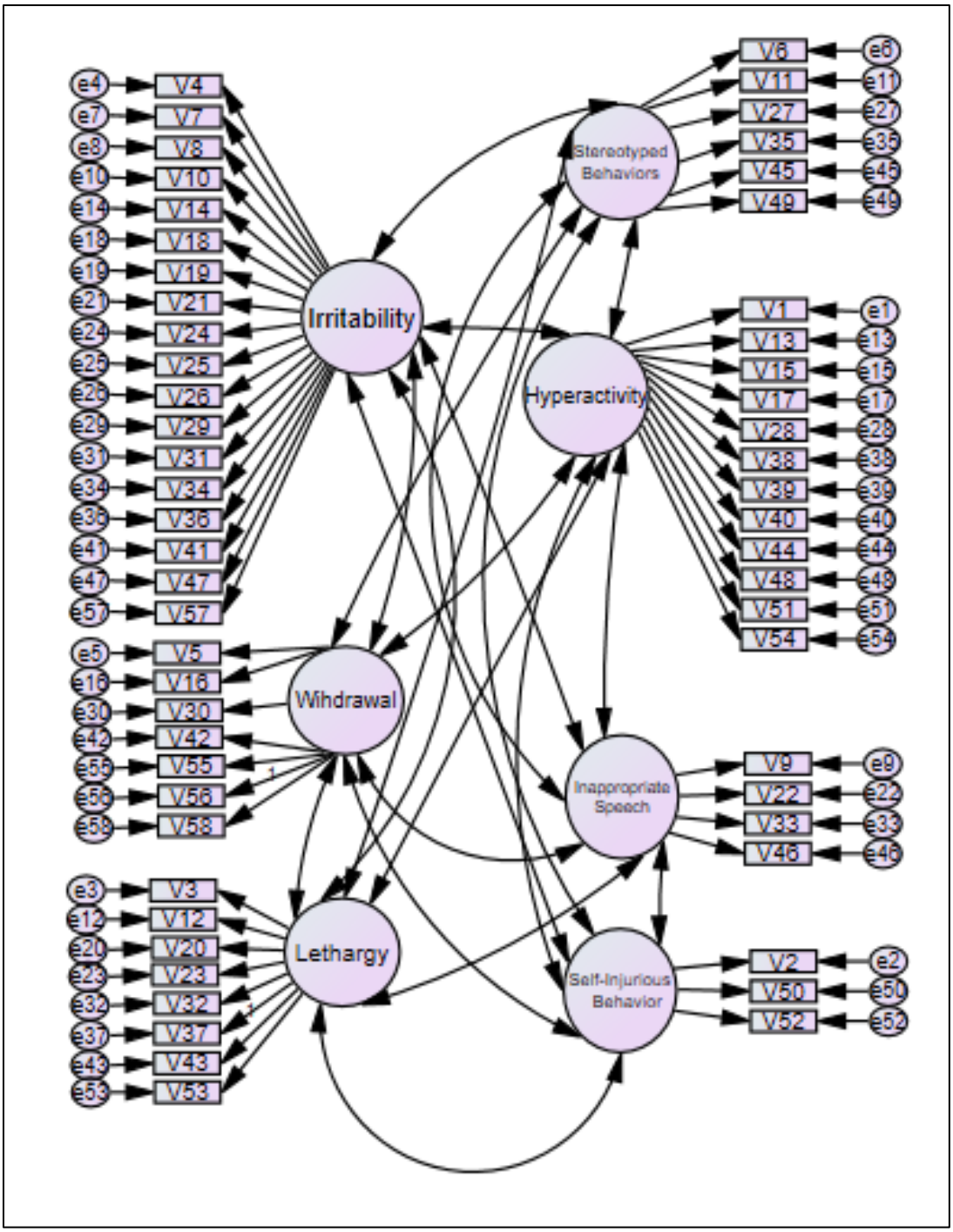
APPENDIX B: EFA Model 2

Figure 16. *Brinkley et al. (2007) five-factor model*



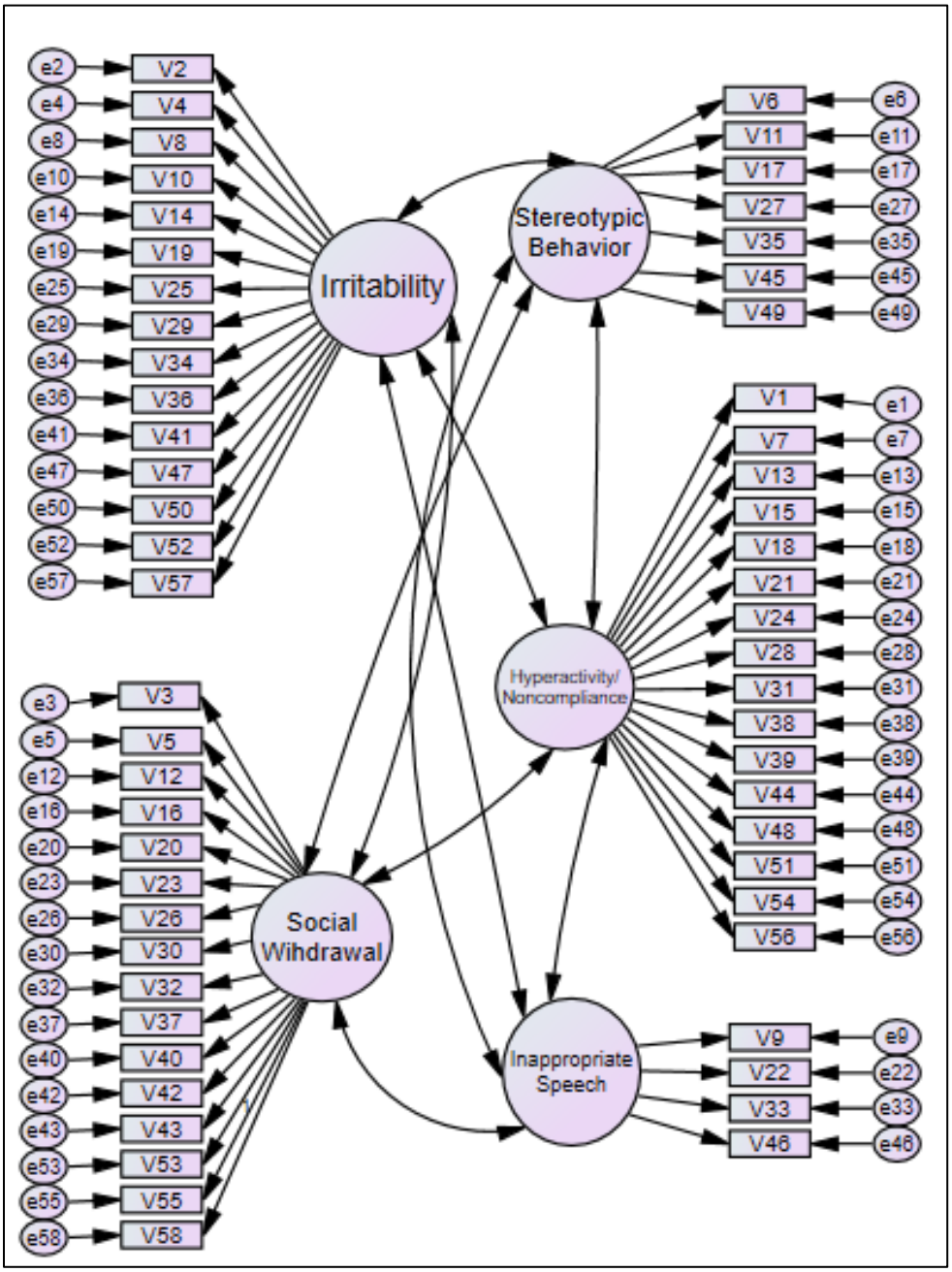
APPENDIX C: EFA Model 3

Figure 17. *Mirwis (2011) seven-factor model*



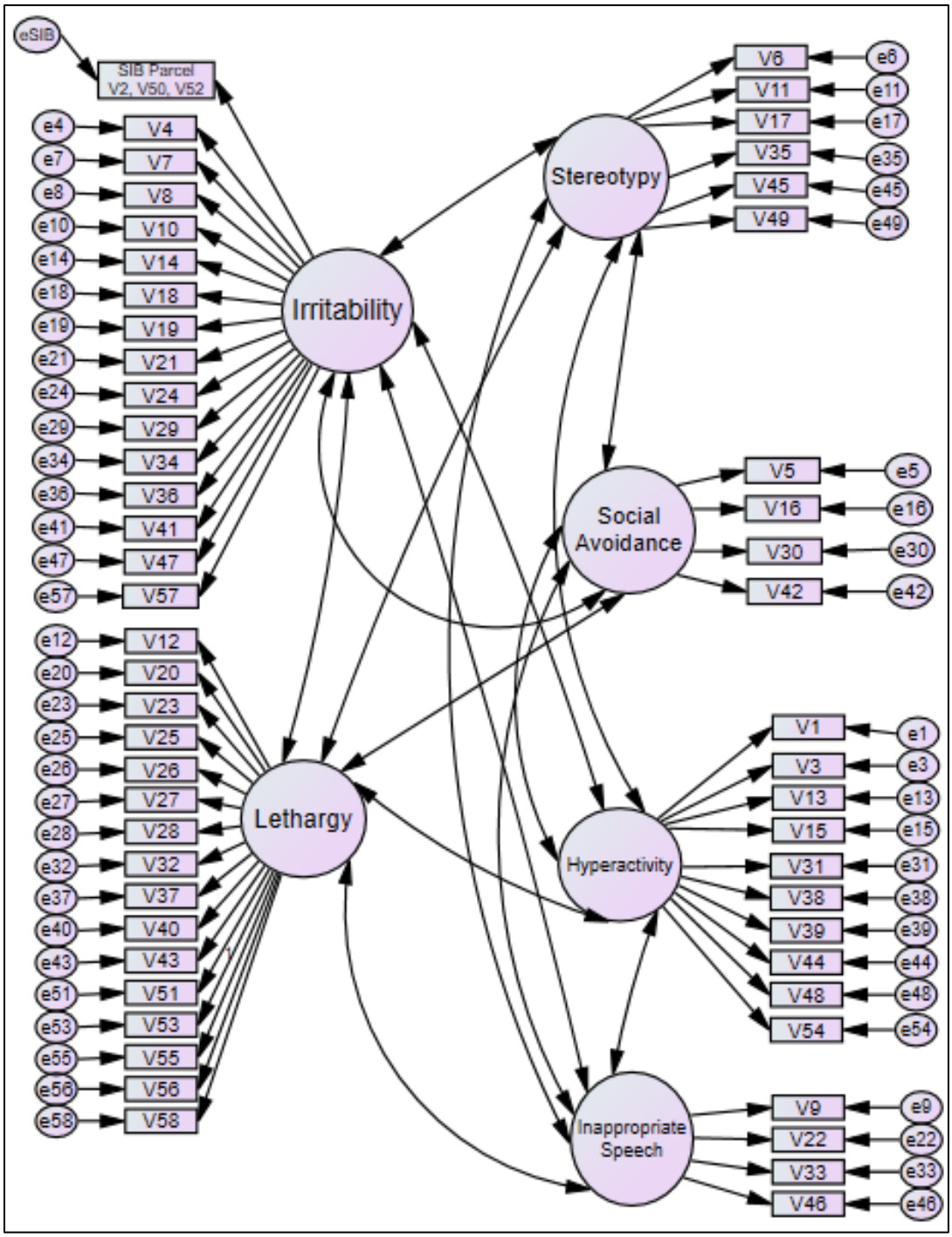
APPENDIX D: EFA Model 4

Figure 18. *Aman et al. (1985a) five-factor model*



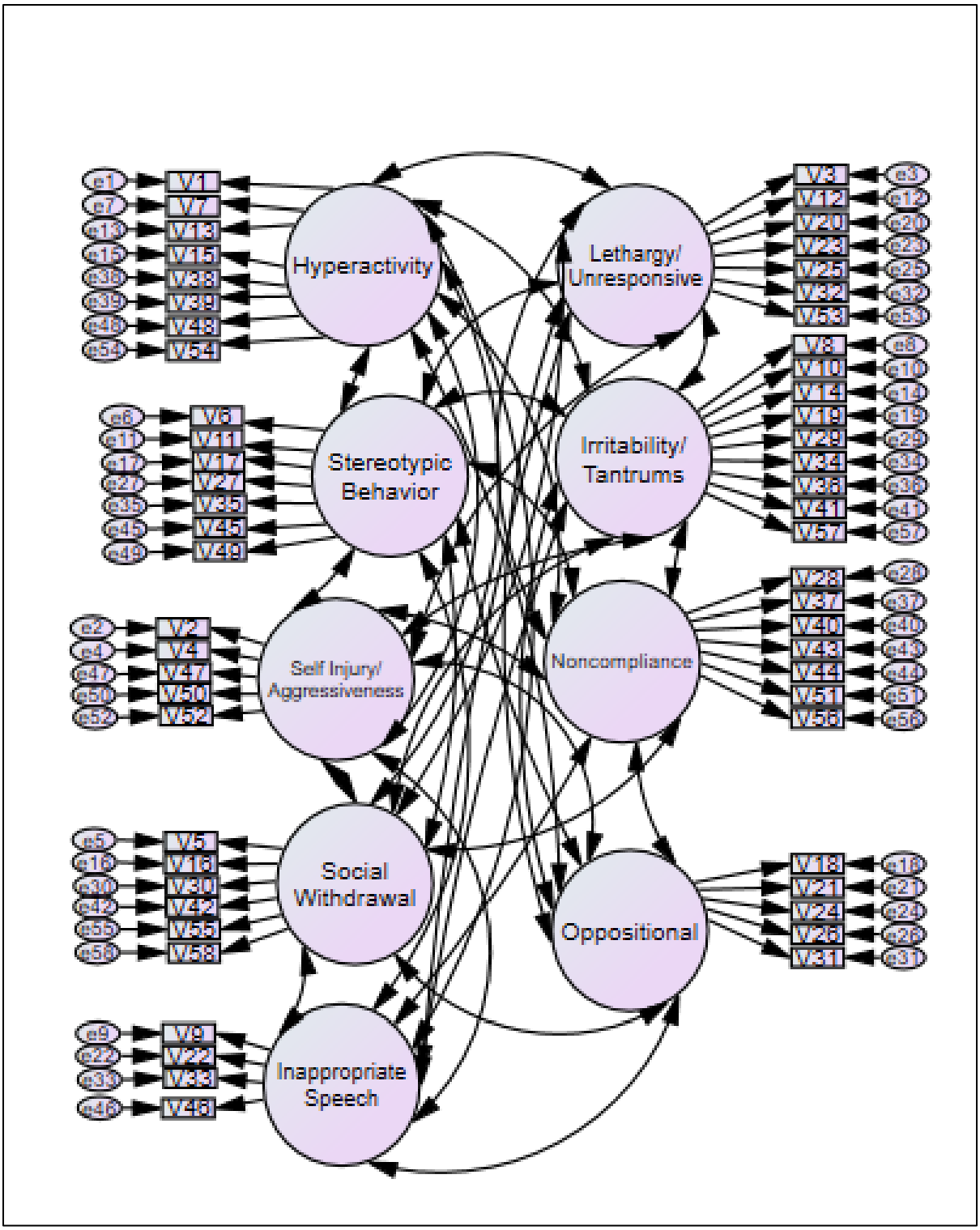
APPENDIX E: EFA Model 5

Figure 19. *Sansone et al. (2012) six-factor model*



APPENDIX F: EFA Model 6

Figure 20. *Study one nine-factor model*



APPENDIX G: Inter-Item Polychoric Correlation Matrix

Table 32. *Study One Inter-Item Polychoric Correlation Matrix (N = 300)*

Item	1	2	3	4	5	6	7	8	9	10
1	(.869)									
2	0.339	(.942)								
3	-0.014	0.256	(.758)							
4	0.408	0.653	0.131	(.722)						
5	0.276	0.235	0.433	0.270	(.895)					
6	0.373	0.464	0.258	0.346	0.524	(.856)				
7	0.671	0.544	0.135	0.619	0.318	0.597	(.791)			
8	0.478	0.479	0.238	0.532	0.364	0.437	0.732	(.910)		
9	0.238	-0.025	-0.028	0.142	0.161	0.237	0.329	0.367	(.723)	
10	0.409	0.686	0.170	0.710	0.317	0.392	0.604	0.702	0.158	(.900)
11	0.398	0.470	0.219	0.363	0.521	0.855	0.565	0.446	0.174	0.460
12	0.227	0.291	0.510	0.210	0.594	0.564	0.376	0.365	0.157	0.285
13	0.617	0.493	0.141	0.584	0.439	0.493	0.682	0.639	0.294	0.598
14	0.354	0.419	0.306	0.480	0.324	0.297	0.456	0.549	0.184	0.679
15	0.747	0.426	0.122	0.438	0.331	0.508	0.703	0.541	0.276	0.494
16	0.266	0.284	0.457	0.251	0.849	0.548	0.386	0.409	0.172	0.368
17	0.495	0.461	0.295	0.380	0.618	0.687	0.611	0.506	0.227	0.467
18	0.553	0.581	0.189	0.722	0.405	0.389	0.651	0.659	0.152	0.785
19	0.508	0.511	0.201	0.503	0.376	0.425	0.725	0.910	0.358	0.719
20	0.293	0.292	0.545	0.265	0.494	0.434	0.429	0.395	0.141	0.357
21	0.576	0.455	0.114	0.614	0.345	0.431	0.791	0.687	0.384	0.626
22	0.190	0.185	0.033	0.246	0.270	0.392	0.446	0.365	0.708	0.319
23	0.023	0.043	0.579	-0.024	0.455	0.220	0.112	0.086	0.039	-0.033
24	0.379	0.479	0.347	0.608	0.537	0.340	0.501	0.545	0.175	0.655
25	0.152	0.294	0.489	0.266	0.460	0.249	0.324	0.333	0.105	0.421
26	0.184	0.171	0.381	0.238	0.488	0.224	0.341	0.266	0.053	0.231
27	0.292	0.332	0.385	0.302	0.423	0.665	0.491	0.304	0.184	0.299
28	0.436	0.311	0.334	0.303	0.632	0.556	0.494	0.450	0.273	0.410
29	0.515	0.479	0.201	0.595	0.415	0.411	0.609	0.600	0.156	0.735
30	0.229	0.227	0.447	0.220	0.895	0.522	0.308	0.325	0.077	0.327
31	0.571	0.493	0.155	0.665	0.406	0.440	0.721	0.740	0.296	0.671
32	0.155	0.118	0.497	0.071	0.394	0.256	0.258	0.208	0.021	0.194
33	0.199	0.206	0.014	0.284	0.336	0.405	0.415	0.415	0.723	0.288
34	0.308	0.381	0.383	0.368	0.430	0.409	0.470	0.549	0.296	0.582
35	0.359	0.392	0.259	0.316	0.482	0.856	0.529	0.355	0.150	0.356
36	0.478	0.619	0.288	0.578	0.399	0.516	0.584	0.578	0.115	0.752
37	0.230	0.334	0.489	0.321	0.537	0.392	0.333	0.368	-0.017	0.350

Table 32 (cont'd)

38	0.658	0.422	0.069	0.419	0.334	0.401	0.556	0.498	0.094	0.502
39	0.616	0.399	0.110	0.377	0.169	0.363	0.551	0.358	0.064	0.386
40	0.367	0.350	0.455	0.333	0.698	0.522	0.431	0.442	0.126	0.403
41	0.482	0.541	0.251	0.490	0.426	0.447	0.629	0.843	0.313	0.771
42	0.224	0.189	0.435	0.215	0.879	0.485	0.338	0.337	0.150	0.281
43	0.250	0.360	0.431	0.205	0.554	0.313	0.365	0.358	-0.157	0.310
44	0.486	0.247	0.242	0.311	0.494	0.461	0.479	0.462	0.338	0.382
45	0.393	0.303	0.326	0.244	0.420	0.726	0.438	0.326	0.041	0.275
46	0.151	0.145	0.151	0.281	0.304	0.324	0.394	0.388	0.641	0.362
47	0.459	0.596	0.139	0.538	0.232	0.369	0.584	0.598	0.293	0.576
48	0.722	0.513	0.129	0.475	0.380	0.542	0.632	0.522	0.198	0.546
49	0.360	0.328	0.317	0.187	0.337	0.703	0.439	0.289	0.139	0.202
50	0.389	0.942	0.248	0.621	0.260	0.468	0.541	0.488	0.044	0.661
51	0.330	0.293	0.359	0.326	0.594	0.469	0.463	0.439	0.164	0.384
52	0.369	0.938	0.217	0.631	0.275	0.470	0.534	0.486	-0.038	0.672
53	0.067	0.161	0.758	0.142	0.451	0.312	0.248	0.275	0.065	0.150
54	0.869	0.474	0.029	0.462	0.338	0.478	0.681	0.472	0.243	0.515
55	0.274	0.336	0.307	0.337	0.509	0.312	0.383	0.218	0.052	0.347
56	0.433	0.333	0.200	0.481	0.583	0.433	0.535	0.511	0.219	0.461
57	0.428	0.627	0.229	0.700	0.379	0.369	0.585	0.696	0.220	0.900
58	0.274	0.293	0.322	0.229	0.651	0.424	0.343	0.347	0.002	0.281

Item	11	12	13	14	15	16	17	18	19	20
11	(.873)									
12	0.607	(.745)								
13	0.557	0.494	(.735)							
14	0.379	0.357	0.505	(.715)						
15	0.496	0.403	0.681	0.541	(.832)					
16	0.597	0.688	0.432	0.411	0.450	(.885)				
17	0.769	0.575	0.665	0.453	0.561	0.668	(.769)			
18	0.458	0.323	0.725	0.628	0.563	0.452	0.588	(.798)		
19	0.458	0.376	0.658	0.564	0.563	0.432	0.582	0.688	(.910)	
20	0.474	0.612	0.420	0.402	0.433	0.602	0.557	0.463	0.465	(.644)
21	0.508	0.314	0.721	0.458	0.567	0.401	0.658	0.746	0.692	0.409
22	0.383	0.243	0.294	0.157	0.234	0.310	0.433	0.273	0.431	0.324
23	0.277	0.599	0.115	0.268	0.197	0.527	0.378	0.077	0.095	0.505
24	0.410	0.365	0.631	0.568	0.449	0.456	0.558	0.798	0.553	0.476
25	0.305	0.414	0.316	0.495	0.270	0.517	0.449	0.473	0.360	0.515
26	0.232	0.349	0.338	0.338	0.419	0.449	0.298	0.357	0.283	0.445

Table 32 (cont'd)

27	0.642	0.480	0.357	0.342	0.393	0.429	0.558	0.375	0.287	0.447
28	0.598	0.654	0.621	0.434	0.544	0.656	0.673	0.530	0.485	0.557
29	0.490	0.378	0.696	0.542	0.522	0.434	0.525	0.703	0.601	0.444
30	0.588	0.607	0.399	0.395	0.361	0.885	0.653	0.405	0.325	0.555
31	0.504	0.334	0.735	0.555	0.582	0.451	0.643	0.769	0.746	0.423
32	0.346	0.421	0.208	0.305	0.178	0.456	0.376	0.320	0.212	0.531
33	0.359	0.271	0.302	0.134	0.298	0.374	0.436	0.302	0.474	0.256
34	0.426	0.410	0.482	0.715	0.431	0.419	0.467	0.483	0.567	0.400
35	0.873	0.612	0.472	0.320	0.476	0.574	0.719	0.362	0.371	0.409
36	0.565	0.517	0.691	0.601	0.535	0.442	0.617	0.675	0.610	0.483
37	0.486	0.652	0.407	0.422	0.389	0.598	0.524	0.426	0.392	0.585
38	0.464	0.328	0.626	0.516	0.766	0.370	0.502	0.647	0.501	0.330
39	0.409	0.274	0.513	0.372	0.785	0.287	0.421	0.483	0.404	0.337
40	0.568	0.659	0.564	0.427	0.519	0.729	0.702	0.512	0.472	0.638
41	0.491	0.390	0.648	0.697	0.551	0.443	0.594	0.686	0.884	0.451
42	0.550	0.599	0.396	0.269	0.331	0.859	0.570	0.346	0.332	0.579
43	0.439	0.590	0.411	0.342	0.390	0.567	0.523	0.360	0.398	0.578
44	0.497	0.578	0.631	0.507	0.599	0.555	0.602	0.479	0.508	0.455
45	0.760	0.506	0.480	0.276	0.515	0.528	0.664	0.307	0.348	0.394
46	0.340	0.265	0.297	0.239	0.230	0.379	0.447	0.314	0.474	0.303
47	0.418	0.284	0.552	0.391	0.492	0.344	0.522	0.596	0.568	0.353
48	0.594	0.386	0.700	0.479	0.779	0.458	0.616	0.617	0.549	0.377
49	0.636	0.479	0.390	0.298	0.510	0.463	0.534	0.282	0.307	0.393
50	0.488	0.331	0.493	0.434	0.448	0.341	0.476	0.556	0.535	0.333
51	0.572	0.682	0.544	0.395	0.477	0.660	0.596	0.483	0.462	0.626
52	0.452	0.311	0.500	0.369	0.401	0.321	0.471	0.557	0.530	0.301
53	0.331	0.745	0.300	0.361	0.271	0.550	0.347	0.223	0.283	0.644
54	0.485	0.262	0.674	0.443	0.832	0.395	0.600	0.590	0.519	0.369
55	0.384	0.396	0.488	0.316	0.456	0.531	0.464	0.443	0.298	0.537
56	0.453	0.469	0.645	0.535	0.459	0.562	0.592	0.636	0.520	0.448
57	0.447	0.304	0.627	0.676	0.481	0.401	0.478	0.758	0.687	0.398
58	0.528	0.621	0.392	0.320	0.420	0.734	0.543	0.395	0.392	0.640

Item	21	22	23	24	25	26	27	28	29	30
21	(.871)									
22	0.479	(.847)								
23	0.107	0.192	(.720)							
24	0.663	0.255	0.322	(.798)						
25	0.363	0.081	0.529	0.574	(.637)					
26	0.380	0.137	0.450	0.538	0.444	(.750)				

Table 32 (cont'd)

27	0.447	0.272	0.358	0.381	0.397	0.258	(.731)			
28	0.546	0.352	0.467	0.601	0.495	0.407	0.502	(.824)		
29	0.663	0.241	0.056	0.647	0.466	0.274	0.353	0.601	(.820)	
30	0.366	0.236	0.558	0.502	0.559	0.506	0.463	0.657	0.476	(.918)
31	0.871	0.368	0.124	0.690	0.407	0.370	0.392	0.568	0.671	0.403
32	0.287	0.082	0.659	0.420	0.637	0.333	0.386	0.426	0.242	0.482
33	0.448	0.734	0.027	0.267	0.146	0.166	0.210	0.314	0.166	0.241
34	0.513	0.379	0.280	0.549	0.390	0.270	0.327	0.531	0.563	0.435
35	0.435	0.339	0.324	0.365	0.329	0.228	0.731	0.551	0.407	0.561
36	0.625	0.184	0.198	0.649	0.501	0.259	0.398	0.550	0.678	0.409
37	0.359	0.076	0.594	0.605	0.588	0.476	0.514	0.678	0.410	0.584
38	0.565	0.125	0.132	0.560	0.287	0.333	0.325	0.550	0.564	0.391
39	0.507	0.092	0.149	0.411	0.159	0.272	0.361	0.450	0.407	0.266
40	0.489	0.245	0.597	0.596	0.551	0.483	0.387	0.755	0.522	0.750
41	0.638	0.378	0.127	0.606	0.390	0.228	0.346	0.542	0.656	0.391
42	0.381	0.243	0.546	0.517	0.554	0.589	0.432	0.637	0.454	0.918
43	0.341	0.024	0.541	0.456	0.416	0.419	0.410	0.577	0.350	0.585
44	0.477	0.345	0.433	0.495	0.347	0.279	0.401	0.719	0.513	0.527
45	0.342	0.190	0.344	0.288	0.192	0.233	0.567	0.476	0.362	0.498
46	0.444	0.847	0.184	0.332	0.126	0.132	0.203	0.396	0.276	0.227
47	0.592	0.321	0.070	0.469	0.354	0.200	0.305	0.424	0.556	0.281
48	0.574	0.226	0.100	0.474	0.254	0.258	0.448	0.574	0.547	0.406
49	0.346	0.122	0.272	0.301	0.240	0.235	0.669	0.429	0.252	0.349
50	0.487	0.193	0.053	0.462	0.296	0.155	0.395	0.349	0.503	0.258
51	0.501	0.242	0.477	0.542	0.451	0.430	0.436	0.824	0.496	0.600
52	0.472	0.156	0.042	0.462	0.299	0.139	0.354	0.350	0.508	0.277
53	0.169	0.037	0.720	0.380	0.524	0.433	0.407	0.536	0.269	0.468
54	0.629	0.283	0.054	0.437	0.173	0.201	0.337	0.484	0.552	0.342
55	0.425	0.218	0.340	0.469	0.430	0.750	0.379	0.486	0.411	0.548
56	0.634	0.295	0.271	0.683	0.419	0.450	0.317	0.743	0.581	0.570
57	0.655	0.292	0.010	0.698	0.411	0.270	0.314	0.504	0.820	0.423
58	0.379	0.187	0.508	0.483	0.388	0.419	0.328	0.653	0.400	0.712

Item	31	32	33	34	35	36	37	38	39	40
31	(.871)									
32	0.230	(.659)								
33	0.384	0.039	(.734)							
34	0.549	0.247	0.350	(.727)						
35	0.457	0.276	0.377	0.398	(.873)					
36	0.648	0.348	0.213	0.600	0.518	(.752)				

Table 32 (cont'd)

37	0.444	0.541	0.069	0.303	0.479	0.469	(.751)			
38	0.609	0.164	0.144	0.408	0.412	0.535	0.444	(.798)		
39	0.539	0.135	0.096	0.331	0.385	0.450	0.417	0.798	(.798)	
40	0.529	0.535	0.268	0.430	0.560	0.570	0.721	0.514	0.458	(.772)
41	0.711	0.200	0.403	0.727	0.430	0.695	0.413	0.576	0.455	0.538
42	0.415	0.507	0.276	0.351	0.508	0.394	0.608	0.313	0.240	0.727
43	0.471	0.450	-0.024	0.335	0.448	0.439	0.684	0.397	0.451	0.742
44	0.538	0.326	0.313	0.507	0.470	0.509	0.575	0.528	0.454	0.626
45	0.396	0.203	0.237	0.314	0.825	0.423	0.392	0.438	0.436	0.566
46	0.362	0.100	0.712	0.406	0.324	0.262	0.145	0.159	0.120	0.301
47	0.599	0.155	0.365	0.424	0.369	0.552	0.307	0.424	0.437	0.361
48	0.578	0.186	0.234	0.402	0.543	0.575	0.437	0.744	0.685	0.477
49	0.411	0.240	0.245	0.287	0.694	0.436	0.427	0.391	0.420	0.376
50	0.493	0.126	0.253	0.389	0.440	0.634	0.359	0.428	0.413	0.352
51	0.546	0.414	0.198	0.401	0.491	0.495	0.751	0.465	0.431	0.772
52	0.489	0.127	0.181	0.336	0.437	0.646	0.362	0.401	0.363	0.373
53	0.186	0.633	-0.005	0.355	0.331	0.397	0.671	0.098	0.179	0.564
54	0.612	0.154	0.286	0.410	0.439	0.542	0.273	0.721	0.730	0.456
55	0.334	0.391	0.168	0.157	0.332	0.478	0.466	0.366	0.349	0.549
56	0.658	0.320	0.267	0.508	0.406	0.529	0.568	0.568	0.360	0.679
57	0.674	0.213	0.294	0.596	0.363	0.728	0.388	0.552	0.422	0.520
58	0.412	0.491	0.210	0.304	0.468	0.433	0.641	0.412	0.370	0.714

Item	41	42	43	44	45	46	47	48	49	50
41	(.884)									
42	0.360	(.981)								
43	0.455	0.613	(.742)							
44	0.561	0.508	0.493	(.719)						
45	0.409	0.477	0.442	0.508	(.825)					
46	0.465	0.239	0.050	0.429	0.234	(.847)				
47	0.604	0.265	0.335	0.357	0.304	0.326	(.665)			
48	0.627	0.348	0.406	0.534	0.550	0.209	0.619	(.812)		
49	0.335	0.406	0.376	0.504	0.695	0.174	0.249	0.496	(.703)	
50	0.587	0.241	0.332	0.307	0.355	0.193	0.665	0.570	0.379	(.958)
51	0.484	0.666	0.703	0.646	0.438	0.307	0.370	0.493	0.428	0.356
52	0.565	0.241	0.356	0.280	0.308	0.143	0.626	0.552	0.321	0.958
53	0.258	0.507	0.568	0.454	0.303	0.175	0.221	0.193	0.342	0.191
54	0.550	0.305	0.317	0.505	0.446	0.206	0.501	0.812	0.414	0.528
55	0.289	0.609	0.430	0.296	0.281	0.235	0.365	0.422	0.254	0.380
56	0.566	0.567	0.435	0.593	0.309	0.354	0.374	0.488	0.351	0.369

Table 32 (cont'd)

57	0.789	0.395	0.371	0.421	0.330	0.365	0.643	0.594	0.249	0.651
58	0.397	0.736	0.685	0.525	0.398	0.164	0.345	0.431	0.374	0.365

Item	51	52	53	54	55	56	57	58
51	(.824)							
52	0.362	(.958)						
53	0.594	0.177	(.758)					
54	0.401	0.490	0.047	(.869)				
55	0.481	0.374	0.419	0.378	(.750)			
56	0.734	0.395	0.317	0.463	0.490	(.743)		
57	0.466	0.645	0.190	0.518	0.414	0.589	(.900)	
58	0.715	0.386	0.538	0.380	0.531	0.545	0.388	(.736)

Note: Prior communalities before rotation are found on the diagonal in parentheses.

APPENDIX H: Nine-Factor Solution Structure Matrix

Table 33. *Study One EFA Nine-Factor Solution Structure Matrix*

		Assigned Factor Number								
Item #	Stem	1	2	3	4	5	6	7	8	9
1	Excessively active at home, school, work, or elsewhere	0.85	0.39	0.35	0.17	0.26	-0.03	0.34	0.31	0.33
2	Injures self on purpose	0.41	0.40	0.95	0.19	0.15	0.12	0.40	0.22	0.32
3	Listless, sluggish, inactive	0.05	0.32	0.22	0.40	0.04	0.78	0.24	0.21	0.10
4	Aggressive to other children or adults (verbally or physically)	0.43	0.30	0.67	0.18	0.28	0.02	0.47	0.25	0.61
5	Seeks isolation from others	0.28	0.47	0.24	0.90	0.30	0.40	0.28	0.49	0.26
6	Meaningless, recurring body movements	0.43	0.89	0.43	0.42	0.39	0.20	0.27	0.35	0.14
7	Boisterous (inappropriately noisy and rough)	0.69	0.54	0.56	0.22	0.50	0.14	0.47	0.37	0.50
8	Screams inappropriately	0.51	0.35	0.53	0.23	0.50	0.14	0.75	0.44	0.39
9	Talks excessively	0.20	0.16	-0.01	0.05	0.81	0.00	0.24	0.09	0.12
10	Temper tantrums / outbursts	0.45	0.33	0.73	0.27	0.32	0.07	0.78	0.29	0.55
11	Stereotyped behavior; abnormal, repetitive movements	0.45	0.89	0.45	0.48	0.35	0.22	0.32	0.47	0.20
12	Preoccupied; stares into space	0.31	0.60	0.30	0.55	0.26	0.59	0.26	0.63	0.08
13	Impulsive (acts without thinking)	0.69	0.49	0.51	0.34	0.37	0.12	0.52	0.54	0.52
14	Irritable and whiny	0.47	0.32	0.40	0.30	0.20	0.34	0.74	0.30	0.41
15	Restless, unable to sit still	0.92	.50	.41	.31	.31	.20	.38	.37	.32
16	Withdrawn; prefers solitary activities	0.37	0.55	0.31	0.87	0.34	0.49	0.29	0.54	0.20
17	Odd, bizarre in behavior	0.54	0.73	0.46	0.55	0.45	0.29	0.39	0.55	0.33
18	Disobedient; difficult to control	0.59	0.36	0.60	0.34	0.31	0.15	0.62	0.42	0.71
19	Yells at inappropriate times	0.54	0.35	0.56	0.26	0.55	0.16	0.73	0.47	0.37
20	Fixed facial expression; lacks emotional responsiveness	0.38	0.44	0.34	0.53	0.29	0.62	0.28	0.50	0.30

Table 33 (cont'd)

21	Disturbs others	0.61	0.44	0.49	0.28	0.54	0.10	0.49	0.45	0.70
22	Repetitive speech	0.18	0.29	0.19	0.21	0.90	0.04	0.21	0.18	0.18
23	Does nothing but sit and watch others	0.12	0.33	-0.01	0.51	0.10	0.81	0.03	0.42	0.07
24	Uncooperative	0.45	0.34	0.47	0.48	0.28	0.36	0.54	0.48	0.72
25	Depressed mood	0.20	0.30	0.29	0.50	0.12	0.62	0.38	0.33	0.48
26	Resists any form of physical contact	0.35	0.19	0.17	0.58	0.15	0.53	0.07	0.22	0.54
27	Moves or rolls head back and forth repetitively	0.35	0.77	0.32	0.32	0.23	0.42	0.20	0.28	0.28
28	Does not pay attention to instructions	0.52	0.55	0.31	0.60	0.37	0.41	0.37	0.77	0.36
29	Demands must be met immediately	0.52	0.39	0.53	0.39	0.25	0.12	0.66	0.46	0.58
30	Isolates himself/herself from other children or adults	0.32	0.52	0.24	0.94	0.21	0.47	0.28	0.49	0.27
31	Disrupts group activities	0.62	0.45	0.51	0.31	0.43	0.10	0.61	0.53	0.64
32	Sits or stands in one position for a long time	0.16	0.31	0.11	0.44	0.07	0.70	0.16	0.35	0.32
33	Talks to self loudly	0.21	0.32	0.23	0.25	0.84	-0.02	0.23	0.13	0.14
34	Cries over minor annoyances and hurts	0.37	0.38	0.35	0.33	0.40	0.30	0.75	0.33	0.26
35	Repetitive hand, body, or head movements	0.41	0.93	0.39	0.45	0.32	0.25	0.25	0.41	0.14
36	Mood changes quickly	0.52	0.51	0.65	0.35	0.23	0.28	0.63	0.45	0.47
37	Unresponsive to structured activities (does not react)	0.36	0.47	0.34	0.54	0.06	0.64	0.25	0.70	0.34
38	Does not stay in seat (e.g., during lesson or training periods, meals, etc.)	0.83	0.41	0.39	0.31	0.14	0.07	0.44	0.45	0.40
39	Will not sit still for any length of time	0.84	0.40	0.38	0.18	0.10	0.14	0.26	0.39	0.27
40	Is difficult to reach, contact, or get through to	0.48	0.52	0.35	0.72	0.25	0.52	0.33	0.73	0.33
41	Cries and screams inappropriately	0.55	0.40	0.59	0.32	0.46	0.17	0.84	0.48	0.32
42	Prefers to be alone	0.29	0.48	0.22	0.93	0.25	0.50	0.18	0.52	0.32
43	Does not try to communicate by words or gestures	0.40	0.41	0.35	0.55	-0.02	0.54	0.24	0.69	0.19

Table 33 (cont'd)

44	Easily distractible	0.56	0.51	0.23	0.43	0.39	0.33	0.44	0.67	0.21
45	Waves or shakes the extremities repeatedly	0.48	0.84	0.30	0.41	0.19	0.24	0.24	0.37	0.03
46	Repeats a word or phrase over and over	0.16	0.27	0.19	0.23	0.85	0.10	0.32	0.25	0.17
47	Stamps feet or bangs objects or slams doors	0.51	0.34	0.67	0.22	0.39	0.11	0.44	0.32	0.38
48	Constantly runs or jumps around the room	0.83	0.56	0.55	0.33	0.26	0.09	0.41	0.42	0.31
49	Rocks body back and forth repeatedly	0.45	0.79	0.28	0.28	0.19	0.30	0.18	0.32	0.08
50	Deliberately hurts himself/herself	0.45	0.44	0.96	0.22	0.20	0.13	0.40	0.25	0.28
51	Pays no attention when spoken to	0.45	0.48	0.33	0.58	0.26	0.46	0.28	0.85	0.32
52	Does physical violence to self	0.40	0.40	0.97	0.23	0.14	0.09	0.38	0.30	0.30
53	Inactive, never moves spontaneously	0.15	0.36	0.17	0.44	0.09	0.87	0.20	0.50	0.13
54	Tends to be excessively active	0.90	0.46	0.48	0.29	0.31	-0.01	0.37	0.33	0.32
55	Responds negatively to affection	0.43	0.29	0.40	0.63	0.19	0.45	0.03	0.28	0.55
56	Deliberately ignores directions	0.48	0.38	0.35	0.54	0.33	0.23	0.44	0.67	0.55
57	Has temper outbursts or tantrums when he/she does not get own way	0.48	0.33	0.70	0.37	0.32	0.10	0.76	0.38	0.57
58	Shows few social reactions to others	0.40	0.42	0.36	0.71	0.16	0.46	0.17	0.68	0.21

APPENDIX I: Brinkley et al. (2007) Four-Factor Model Study Two CFA Statistics

Table 34. *Brinkley et al. (2007) Four-Factor Model Parameter Estimates, Standard Errors, Two-Tailed p-Value, R^2, Residual Variance*

Factor	Item #	Parameter Estimate	Standard Error (S.E.)	Parameter Estimate/ Standard Error (S.E.)	Two-Tailed *p*-Value	R^2	Residual Variance
Hyperactivity							
	34	1.000	0.000	[a]	[a]	1.000	0.000
	1	0.805	0.026	31.206	< .001	0.648	0.352
	4	0.706	0.036	19.476	< .001	0.499	0.501
	7	0.833	0.022	38.127	< .001	0.693	0.307
	8	0.828	0.024	33.899	< .001	0.685	0.315
	9	0.348	0.063	5.481	< .001	0.121	0.879
	10	0.872	0.019	47.03	< .001	0.761	0.239
	13	0.765	0.030	25.519	< .001	0.585	0.415
	14	0.769	0.030	25.679	< .001	0.591	0.409
	15	0.836	0.022	37.162	< .001	0.699	0.301
	18	0.867	0.020	42.933	< .001	0.751	0.249
	19	0.844	0.022	38.558	< .001	0.713	0.287
	21	0.796	0.028	28.812	< .001	0.634	0.366
	24	0.869	0.018	48.658	< .001	0.755	0.245
	28	0.807	0.028	29.038	< .001	0.652	0.348
	29	0.814	0.026	30.995	< .001	0.663	0.337
	31	0.838	0.021	39.655	< .001	0.702	0.298
	33	0.450	0.058	7.700	< .001	0.202	0.798
	36	0.848	0.023	37.006	< .001	0.720	0.280
	38	0.817	0.026	31.581	< .001	0.668	0.332
	39	0.813	0.029	28.215	< .001	0.661	0.339
	41	0.826	0.026	31.737	< .001	0.683	0.317
	44	0.647	0.040	15.989	< .001	0.419	0.581
	47	0.780	0.031	24.876	< .001	0.609	0.391
	48	0.799	0.030	26.908	< .001	0.638	0.362
	51	0.807	0.026	31.159	< .001	0.651	0.349
	54	0.857	0.022	38.358	< .001	0.734	0.266
	56	0.784	0.028	27.709	< .001	0.615	0.385
	57	0.839	0.022	38.097	< .001	0.704	0.296
Lethargy							
	3	0.482	0.068	7.086	< .001	0.232	0.768
	5	0.875	0.020	43.348	< .001	0.766	0.234
	16	0.877	0.021	41.351	< .001	0.769	0.231

Table 34 (cont'd)

	20	0.742	0.040	18.442	< .001	0.550	0.45
	23	0.558	0.062	9.021	< .001	0.312	0.688
	25	0.677	0.059	11.544	< .001	0.458	0.542
	26	0.749	0.045	16.475	< .001	0.561	0.439
	30	0.933	0.014	64.542	< .001	0.871	0.129
	32	0.758	0.044	17.192	< .001	0.574	0.426
	37	0.888	0.029	31.094	< .001	0.789	0.211
	40	0.872	0.039	22.312	< .001	0.761	0.239
	42	0.845	0.024	34.935	< .001	0.714	0.286
	43	0.790	0.044	18.089	< .001	0.623	0.377
	53	0.635	0.069	9.221	< .001	0.403	0.597
	55	0.730	0.056	13.090	< .001	0.532	0.468
	58	0.783	0.034	23.091	< .001	0.612	0.388
Stereotypy							
	6	0.905	0.019	48.313	< .001	0.819	0.181
	11	0.918	0.018	51.763	< .001	0.843	0.157
	12	0.802	0.036	22.524	< .001	0.644	0.356
	17	0.936	0.026	35.717	< .001	0.876	0.124
	22	0.697	0.040	17.304	< .001	0.486	0.514
	27	0.793	0.047	16.942	< .001	0.629	0.371
	35	0.854	0.022	39.132	< .001	0.730	0.270
	45	0.793	0.034	23.648	< .001	0.629	0.371
	46	0.770	0.038	20.469	< .001	0.593	0.407
	49	0.748	0.047	15.878	< .001	0.560	0.440
Irritability							
	2	0.975	0.007	147.411	< .001	0.648	0.352
	50	0.995	0.005	188.284	< .001	0.990	0.010
	52	0.969	0.008	122.970	< .001	0.938	0.062

[a] Indicates a factor loading fixed to 1.0 because of a near zero, negative residual.

APPENDIX J: Brinkley et al (2007) Five-Factor Model Study Two CFA Statistics

Table 35. *Brinkley et al. (2007) Five-Factor Model Parameter Estimates, Standard Errors, Two-Tailed p-Value, R^2, Residual Variance*

Factor	Item #	Parameter Estimate	Standard Error (S.E.)	Parameter Estimate/ Standard Error (S.E.)	Two-Tailed *p*-Value	R^2	Residual Variance
Hyperactivity							
	1	0.809	0.026	31.356	< .001	0.654	0.346
	4	0.710	0.036	19.568	< .001	0.505	0.495
	7	0.837	0.022	38.432	< .001	0.700	0.300
	8	0.833	0.024	34.229	< .001	0.693	0.307
	10	0.876	0.019	47.332	< .001	0.767	0.233
	13	0.769	0.030	25.688	< .001	0.591	0.409
	14	0.779	0.030	25.621	< .001	0.607	0.393
	15	0.839	0.022	37.641	< .001	0.705	0.295
	18	0.870	0.020	43.305	< .001	0.757	0.243
	19	0.848	0.022	38.753	< .001	0.718	0.282
	21	0.799	0.028	28.998	< .001	0.638	0.362
	24	0.874	0.018	49.230	< .001	0.764	0.236
	28	0.812	0.028	29.279	< .001	0.660	0.340
	29	0.820	0.026	31.245	< .001	0.673	0.327
	31	0.842	0.021	40.041	< .001	0.709	0.291
	36	0.855	0.023	37.238	< .001	0.730	0.270
	38	0.820	0.026	31.860	< .001	0.673	0.327
	39	0.816	0.029	28.433	< .001	0.666	0.334
	41	0.834	0.026	31.794	< .001	0.695	0.305
	44	0.654	0.041	16.043	< .001	0.428	0.572
	47	0.787	0.031	25.135	< .001	0.619	0.381
	48	0.803	0.030	27.197	< .001	0.645	0.355
	51	0.813	0.026	31.462	< .001	0.661	0.339
	54	0.859	0.022	38.572	< .001	0.739	0.261
	56	0.790	0.028	27.916	< .001	0.623	0.377
	57	0.844	0.022	38.153	< .001	0.712	0.288
Lethargy							
	3	0.483	0.068	7.104	< .001	0.233	0.767
	5	0.875	0.020	43.420	< .001	0.766	0.234
	16	0.876	0.021	41.199	< .001	0.768	0.232
	20	0.742	0.040	18.467	< .001	0.550	0.450
	23	0.559	0.062	9.036	< .001	0.312	0.688
	25	0.677	0.059	11.512	< .001	0.459	0.541

Table 35 (cont'd)

	26	0.749	0.045	16.472	< .001	0.562	0.438
	30	0.933	0.015	64.110	< .001	0.870	0.130
	32	0.757	0.044	17.134	< .001	0.573	0.427
	37	0.889	0.028	31.285	< .001	0.789	0.211
	40	0.872	0.039	22.393	< .001	0.761	0.239
	42	0.845	0.024	34.853	< .001	0.713	0.287
	43	0.791	0.044	18.160	< .001	0.625	0.375
	53	0.634	0.069	9.210	< .001	0.403	0.597
	55	0.731	0.056	13.093	< .001	0.535	0.465
	58	0.783	0.034	23.103	< .001	0.612	0.388
Stereotypy							
	6	0.908	0.018	49.978	< .001	0.825	0.175
	11	0.921	0.018	51.737	< .001	0.848	0.152
	12	0.811	0.036	22.704	< .001	0.658	0.342
	17	0.943	0.028	33.836	< .001	0.889	0.111
	27	0.802	0.047	17.054	< .001	0.643	0.357
	35	0.859	0.021	40.127	< .001	0.739	0.261
	45	0.800	0.033	24.170	< .001	0.640	0.360
	49	0.758	0.047	16.072	< .001	0.575	0.425
Irritability							
	2	0.975	0.007	148.302	< .001	0.950	0.050
	50	0.995	0.005	187.331	< .001	0.990	0.010
	52	0.968	0.008	122.620	< .001	0.938	0.062
Inappropriate Speech							
	34	1.000	0.000	[a]	[a]	1.000	0.000
	9	0.615	0.059	10.502	< .001	0.378	0.622
	22	0.854	0.031	27.283	< .001	0.729	0.271
	33	0.729	0.055	13.370	< .001	0.531	0.469
	46	0.941	0.027	35.129	< .001	0.886	0.114

[a] Indicates a factor loading fixed to 1.0 because of a near zero, negative residual.

APPENDIX K: Aman et al. (1985a) Five-Factor Model Study Two CFA Statistics

Table 36. *Aman et al. (1985a) Five-Factor Model Parameter Estimates, Standard Errors, Two-Tailed p-Value, R^2, Residual Variance*

Factor	Item #	Parameter Estimate	Standard Error (S.E.)	Parameter Estimate/ Standard Error (S.E.)	Two-Tailed *p*-Value	R^2	Residual Variance
Irritability							
	2	0.936	0.009	100.271	< .001	0.876	0.124
	4	0.741	0.035	20.907	< .001	0.549	0.451
	8	0.866	0.024	36.830	< .001	0.751	0.249
	10	0.916	0.016	56.129	< .001	0.838	0.162
	14	0.820	0.029	28.439	< .001	0.672	0.328
	19	0.887	0.022	41.134	< .001	0.786	0.214
	25	0.629	0.062	10.102	< .001	0.395	0.605
	29	0.863	0.025	34.553	< .001	0.745	0.255
	34	0.719	0.038	18.792	< .001	0.518	0.482
	36	0.899	0.022	40.147	< .001	0.809	0.191
	41	0.867	0.025	34.778	< .001	0.752	0.248
	47	0.826	0.031	26.686	< .001	0.682	0.318
	50	0.986	0.006	165.461	< .001	0.972	0.028
	52	0.941	0.010	97.571	< .001	0.885	0.115
	57	0.882	0.020	43.125	< .001	0.778	0.222
Lethargy, Social Withdrawal							
	3	0.479	0.068	7.052	< .001	0.229	0.771
	5	0.874	0.020	43.115	< .001	0.763	0.237
	12	0.805	0.034	23.544	< .001	0.649	0.351
	16	0.872	0.021	40.992	< .001	0.761	0.239
	20	0.738	0.041	18.196	< .001	0.544	0.456
	23	0.556	0.062	8.999	< .001	0.309	0.691
	26	0.745	0.046	16.180	< .001	0.555	0.445
	30	0.931	0.015	63.342	< .001	0.867	0.133
	32	0.751	0.044	16.966	< .001	0.564	0.436
	37	0.879	0.028	31.096	< .001	0.773	0.227
	40	0.865	0.037	23.252	< .001	0.748	0.252
	42	0.842	0.024	34.597	< .001	0.709	0.291
	43	0.787	0.044	18.063	< .001	0.619	0.381
	53	0.631	0.069	9.144	< .001	0.398	0.602
	55	0.727	0.057	12.852	< .001	0.529	0.471

Table 36 (cont'd)

	58	0.778	0.034	22.793	< .001	0.605	0.395
Stereotypic Behavior							
	6	0.915	0.018	51.283	< .001	0.838	0.162
	11	0.929	0.018	52.512	< .001	0.864	0.136
	17	0.963	0.030	32.536	< .001	0.928	0.072
	27	0.813	0.047	17.391	< .001	0.661	0.339
	35	0.869	0.021	41.248	< .001	0.755	0.245
	45	0.811	0.033	24.731	< .001	0.657	0.343
	49	0.770	0.047	16.536	< .001	0.593	0.407
Hyperactivity/ Noncompliance							
	1	0.822	0.025	32.467	< .001	0.676	0.234
	7	0.863	0.021	40.138	< .001	0.744	0.256
	13	0.791	0.029	26.890	< .001	0.626	0.374
	15	0.851	0.022	39.588	< .001	0.725	0.275
	18	0.898	0.020	44.558	< .001	0.806	0.194
	21	0.822	0.028	29.833	< .001	0.675	0.325
	24	0.905	0.017	51.911	< .001	0.819	0.181
	28	0.827	0.027	30.449	< .001	0.685	0.315
	31	0.862	0.020	42.368	< .001	0.744	0.256
	38	0.837	0.025	33.574	< .001	0.701	0.299
	39	0.833	0.028	29.665	< .001	0.693	0.307
	44	0.671	0.041	16.336	< .001	0.451	0.549
	48	0.824	0.029	28.860	< .001	0.679	0.321
	51	0.830	0.026	32.329	< .001	0.690	0.310
	54	0.870	0.022	40.153	< .001	0.756	0.244
	56	0.809	0.028	28.827	< .001	0.654	0.346
Inappropriate Speech							
	46	1.000	0.000	[a]	[a]	1.000	0.000
	9	0.701	0.056	12.447	< .001	0.491	0.509
	22	0.896	0.027	33.741	< .001	0.803	0.197
	33	0.830	0.053	15.556	< .001	0.689	0.311

[a] Indicates a factor loading fixed to 1.0 because of a near zero, negative residual.

APPENDIX L: Sansone et al. (2012) Six-Factor Model Study Two CFA Statistics

Table 37. *Sansone et al. (2012) Six-Factor Model Parameter Estimates, Standard Errors, Two-Tailed p-Value, R^2, Residual Variance*

Factor	Item #	Parameter Estimate	Standard Error (S.E.)	Parameter Estimate/ Standard Error (S.E.)	Two-Tailed *p*-Value	R^2	Residual Variance
Irritability							
	4	0.726	0.036	19.986	< .001	0.528	0.472
	7	0.869	0.021	40.788	< .001	0.756	0.244
	8	0.853	0.023	36.606	< .001	0.728	0.272
	10	0.892	0.018	50.865	< .001	0.796	0.204
	14	0.802	0.029	27.576	< .001	0.643	0.357
	18	0.897	0.019	46.070	< .001	0.805	0.195
	19	0.869	0.021	41.535	< .001	0.755	0.245
	21	0.832	0.027	30.307	< .001	0.692	0.308
	24	0.907	0.017	53.036	< .001	0.822	0.178
	29	0.845	0.025	33.428	< .001	0.714	0.286
	34	0.708	0.038	18.539	< .001	0.501	0.499
	36	0.879	0.022	39.303	< .001	0.773	0.227
	41	0.855	0.025	34.346	< .001	0.731	0.269
	47	0.808	0.031	25.788	< .001	0.652	0.348
	57	0.864	0.021	41.127	< .001	0.746	0.254
	59	0.675	0.048	14.056	< .001	0.456	0.544
Hyperactivity							
	1	0.855	0.023	36.766	< .001	0.731	0.269
	3	0.390	0.076	5.1270	< .001	0.152	0.848
	13	0.842	0.029	28.856	< .001	0.709	0.291
	15	0.884	0.019	46.543	< .001	0.782	0.218
	31	0.936	0.021	43.580	< .001	0.876	0.124
	32	-0.202	0.086	-2.364	< .001	0.598	0.402
	38	0.880	0.022	39.584	< .001	0.775	0.225
	39	0.864	0.026	33.476	< .001	0.746	0.254
	44	0.723	0.044	16.564	< .001	0.522	0.478
	48	0.866	0.025	34.636	< .001	0.751	0.249
	54	0.898	0.019	46.826	< .001	0.806	0.194
Socially Unresponsive/ Lethargic							
	12	0.758	0.033	23.193	< .001	0.575	0.425
	20	0.709	0.042	17.005	< .001	0.503	0.497

Table 37 (cont'd)

	23	0.523	0.061	8.546	< .001	0.274	0.726
	25	0.646	0.059	10.921	< .001	0.418	0.582
	26	0.721	0.047	15.178	< .001	0.519	0.481
	27	0.754	0.049	15.334	< .001	0.568	0.432
	28	0.866	0.025	34.050	< .001	0.749	0.251
	32	0.891	0.069	12.830	< .001	0.598	0.402
	37	0.837	0.029	29.157	< .001	0.701	0.299
	40	0.803	0.033	24.293	< .001	0.645	0.355
	43	0.747	0.042	17.770	< .001	0.558	0.442
	51	0.867	0.020	43.038	< .001	0.752	0.248
	53	0.596	0.068	8.706	< .001	0.355	0.645
	55	0.706	0.057	12.467	< .001	0.499	0.501
	56	0.874	0.029	30.352	< .001	0.765	0.235
	58	0.753	0.035	21.409	< .001	0.568	0.432
Social Avoidance							
	5	0.919	0.017	53.443	< .001	0.844	0.156
	16	0.938	0.018	51.814	< .001	0.880	0.120
	30	0.973	0.013	75.062	< .001	0.946	0.054
	42	0.891	0.021	41.841	< .001	0.793	0.207
Stereotypy							
	6	0.915	0.018	51.545	< .001	0.837	0.163
	11	0.928	0.017	53.635	< .001	0.862	0.138
	17	0.964	0.030	32.509	< .001	0.929	0.071
	35	0.869	0.021	41.072	< .001	0.756	0.244
	45	0.814	0.032	25.156	< .001	0.663	0.337
	49	0.775	0.049	15.771	< .001	0.600	0.400
Inappropriate Speech							
	46	1.000	0.000	[a]	[a]	1.000	0.000
	9	0.706	0.056	12.697	< .001	0.498	0.502
	22	0.896	0.026	33.961	< .001	0.803	0.197
	33	0.830	0.052	15.841	< .001	0.690	0.310

[a] Indicates a factor loading fixed to 1.0 because of a near zero, negative residual.

APPENDIX M: Mirwis (2011) Seven-Factor Model Study Two CFA Statistics

Table 38. *Mirwis (2011) Seven-Factor Model Parameter Estimates, Standard Errors, Two-Tailed p-Value, R^2, Residual Variance*

Factor	Item #	Parameter Estimate	Standard Error (S.E.)	Parameter Estimate/ Standard Error (S.E.)	Two-Tailed *p*-Value	R^2	Residual Variance
Irritability							
	4	0.730	0.036	20.630	< .001	0.532	0.468
	7	0.862	0.022	39.793	< .001	0.743	0.257
	8	0.848	0.024	35.732	< .001	0.719	0.281
	10	0.891	0.017	50.978	< .001	0.794	0.206
	14	0.797	0.029	27.457	< .001	0.635	0.365
	18	0.889	0.019	45.581	< .001	0.790	0.210
	19	0.863	0.021	40.599	< .001	0.745	0.255
	21	0.818	0.027	30.059	< .001	0.670	0.330
	24	0.896	0.017	51.861	< .001	0.803	0.197
	25	0.615	0.060	10.318	< .001	0.379	0.621
	26	0.673	0.052	13.030	< .001	0.453	0.547
	29	0.839	0.025	32.935	< .001	0.704	0.296
	31	0.865	0.021	42.045	< .001	0.748	0.252
	34	0.702	0.038	18.259	< .001	0.492	0.508
	36	0.875	0.022	39.197	< .001	0.766	0.234
	41	0.851	0.025	33.422	< .001	0.724	0.276
	47	0.808	0.031	25.969	< .001	0.653	0.347
	57	0.860	0.021	40.955	< .001	0.740	0.260
Hyperactivity							
	1	0.838	0.025	34.065	< .001	0.703	0.297
	13	0.821	0.029	27.913	< .001	0.674	0.326
	15	0.870	0.020	42.803	< .001	0.757	0.243
	17	0.851	0.027	31.518	< .001	0.725	0.275
	28	0.852	0.027	31.378	< .001	0.727	0.273
	38	0.859	0.024	36.372	< .001	0.737	0.263
	39	0.850	0.027	31.560	< .001	0.723	0.277
	40	0.781	0.035	22.220	< .001	0.610	0.390
	44	0.695	0.041	17.097	< .001	0.483	0.517
	48	0.851	0.027	32.062	< .001	0.724	0.276
	51	0.854	0.025	34.181	< .001	0.729	0.271
	54	0.883	0.021	42.782	< .001	0.780	0.220
Withdrawal							
	5	0.886	0.019	46.047	< .001	0.784	0.216

Table 38 (cont'd)

	16	0.889	0.020	44.091	< .001	0.790	0.210
	30	0.944	0.014	67.104	< .001	0.891	0.109
	42	0.852	0.023	36.482	< .001	0.726	0.274
	55	0.749	0.059	12.714	< .001	0.561	0.439
	56	0.981	0.041	23.841	< .001	0.963	0.037
	58	0.803	0.036	22.088	< .001	0.645	0.355
Lethargy							
	3	0.500	0.069	7.195	< .001	0.250	0.750
	12	0.844	0.036	23.655	< .001	0.712	0.288
	20	0.780	0.042	18.420	< .001	0.609	0.391
	23	0.580	0.063	9.212	< .001	0.336	0.664
	32	0.784	0.044	17.791	< .001	0.615	0.385
	37	0.928	0.029	32.210	< .001	0.861	0.139
	43	0.828	0.044	18.642	< .001	0.686	0.314
	53	0.662	0.070	9.475	< .001	0.439	0.561
Stereotyped Behaviors							
	6	0.934	0.018	52.979	< .001	0.873	0.127
	11	0.950	0.018	53.930	< .001	0.902	0.098
	27	0.849	0.047	18.259	< .001	0.721	0.279
	35	0.892	0.020	43.750	< .001	0.796	0.204
	45	0.838	0.032	26.393	< .001	0.702	0.298
	49	0.802	0.046	17.506	< .001	0.643	0.357
Inappropriate Speech							
	46	1.000	0.000	[a]	[a]	1.000	0.000
	9	0.708	0.055	12.765	< .001	0.501	0.499
	22	0.896	0.026	33.859	< .001	0.802	0.198
	33	0.831	0.052	15.871	< .001	0.691	0.309
Self-Injurious Behavior							
	2	0.975	0.007	147.880	< .001	0.951	0.049
	50	0.995	0.005	189.340	< .001	0.989	0.011
	52	0.969	0.008	122.751	< .001	0.938	0.062

[a] Indicates a factor loading fixed to 1.0 because of a near zero, negative residual.

REFERENCES

REFERENCES

Abbeduto, L, McDuffie, A., & Thurman, A. J. (2014). The Fragile X syndrome—autism comorbidity: What do we really know? *Frontiers in Genetics, 5*, 355. doi:10.3389/fgene.2014.00355

Achenbach, T. M., & Rescorla, L. A. (2000). *Manual for the ASEBA preschool forms and profiles*. Burlington, VT: University of Vermont, Research Center for Children, Youth, & Families.

Achenbach, T. M., & Rescorla, L. A. (2001). *Manual for the ASEBA school-age forms and profiles.* Burlington, VT: University of Vermont, Research Center for Children, Youth, & Families.

Allen, R. A., Robins, D. L., & Decker, S. L. (2008). Autism spectrum disorders: Neurobiology and current assessment practices. *Psychology in the Schools, 45*(10), 905-917. doi:10.1002/pits.20341

Allison, P. D. (2002). *Quantitative applications in the social sciences: Missing data.* Thousand Oaks, CA: Sage Publications Ltd. doi:10.4135/9781412985079

Aman, M. G., Burrow, W. H., & Wolford, P. L. (1995). The Aberrant Behavior Checklist-Community: Factor validity and effect of subject variables for adults in group homes. *American Journal of Mental Retardation, 100*(3), 283-292.

Aman, M. G., Richmond, G., Stewart, A. W., Bell, J. C., Kissel, R. C. (1987). The Aberrant Behavior Checklist: Factor structure and the effect of subject variables in American and New Zealand facilities. *American Journal of Mental Deficiency, 91*(6), 570-578.

Aman, M. G., & Singh, N. N. (1986). *Aberrant Behavior Checklist: Manual.* East Aurora, NY: Slosson Educational Publications, Inc.

Aman, M. G., & Singh, N. N. (1994). *Aberrant Behavior Checklist—Community: Supplementary manual*. East Aurora, NY: Slosson Educational Publications, Inc.

Aman, M. G., & Singh, N. N. (2017). *Aberrant Behavior Checklist Manual (2nd ed.).* East Aurora, NY: Slosson Educational Productions, Inc.

Aman, M. G., Singh, N. N., Stewart, A. W., & Field, C. J. (1985b). Psychometric characteristics of the Aberrant Behavior Checklist. *American Journal of Mental Deficiency, 89*(5), 492-502.

Aman, M. G., Singh, N. N., Stewart, A. W., & Field, C. J. (1985a). The Aberrant Behavior

Checklist: A behavior rating scale for the assessment of treatment effects. *American Journal of Mental Deficiency, 89*(5), 485-491.

American Psychiatric Association (1994). *Diagnostic and statistical manual of mental disorders* (4rd ed.). Washington, DC: Author.

American Psychiatric Association (2000). *Diagnostic and statistical manual of mental disorders* (4rd ed., text rev.). Washington, DC: Author.

American Psychiatric Association (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). Washington, DC: Author.

Amir, R. E., Van den Veyver, I. B., Wan, M., Tran, C. Q., Francke, U., & Zoghbi, H. Y. (1999). Rett syndrome is caused by mutations in X-linked MECP2, encoding methyl-CpG-binding protein 2. *Nature Genetics, 23*(2), 185-188. doi:10.1038/13810

Araten-Bergman, T. (2015). The subjective well-being of individuals diagnosed with comorbid intellectual disability and attention deficit hyperactivity disorders. *Quality of Life Research, 24*(8), 1875-1886. doi:10.1007/s11136-015-1036-1

Baio, J., Wiggins, L., Christensen, D. L., Maenner, M. J., Daniels, J., Warren, Z., . . . Dowling, N. F. (2018). Prevalence of autism spectrum disorders among children aged 8 years—Autism and developmental disabilities monitoring network, 11 sites, United States, 2014. *Morbidity and Mortality Weekly Report Surveillance Summaries, 67*(6), 1-23. doi:10.15585/mmwr.ss6706a1

Bartlett, M. S. (1950). Tests of significance in factor analysis. *British Journal of Mathematical and Statistical Psychology, 3*(2), 77-85. doi:10.1111/j.2044-8317.1950.tb00285.x

Basto, M., & Pereira, J. M. (2012). An SPSS R-menu for ordinal factor analysis. *Journal of Statistical Software, 46*(4), 1-29. doi:10.18637/jss.v046.i04

Bayley, N. (1969). *Bayley Scales of Infant Development*. San Antonio, TX: The Psychological Corporation.

Bayley, N. (1993). *Bayley Scales of Infant Development—Second Edition.* San Antonio, TX: The Psychological Corporation.

Bayley, N. (2006). *Bayley Scales of Infant and Toddler Development-Third Edition*. San Antonio, TX: Harcourt Assessment

Beavers, A. S., Lounsbury, J. W., Richards, J. K., Huck, S. W., Skolits, G. J., & Esquivel, S. L. (2013). Practical considerations for using exploratory factor analysis in educational research. *Practical Assessment, Research & Evaluation, 18*(6), Retrieved from http://pareonline.net/getvn.asp?v=18&n=6

Ben-Sasson, A., Cermak, S. A., Orsmond, G. I., Tager-Flusberg, H., Kadlec, M. B., & Carter, A. S. (2008). Sensory clusters of toddlers with autism spectrum disorders: Differences in affective symptoms. *Journal of Child Psychology and Psychiatry, 49*(8), 817-825. doi:10.1111/j.1469-7610.2008.01899.x

Bihm, E. M., & Poindexter, A. R. (1991). Cross-validation of the factor structure of the Aberrant Behavior Checklist for persons with mental retardation. *American Journal of Mental Retardation, 96*(2), 209-211.

Bodfish, J. W., Symons, F. J., Parker, D. E., & Lewis, M. H. (2000). Varieties of repetitive behavior in autism: Comparisons to mental retardation. *Journal of Autism and Developmental Disorders, 30*(3), 237-243. doi:10.1023/A:1005596502855

Bolte, E. E., & Diehl, J. J. (2013). Measurement tools and target symptoms/skills used to assess treatment response for individuals with autism spectrum disorder. *Journal of Autism and Developmental Disorders, 43*(11), 2491-2501. doi:10.1007/s10803-013-1798-7

Bracken, B. A., & McCallum, R. S. (1998). *The Universal Nonverbal Intelligence Test.* Chicago, IL: Riverside.

Brinkley, J., Nations, L., Abramson, R. K., Hall, A., Wright, H. H., Gabriels, R., . . . Cuccaro, M. L. (2007). Factor analysis of the Aberrant Behavior Checklist in individuals with autism spectrum disorders. *Journal of Autism and Developmental Disorders, 37*(10), 1949-1959. doi:10.1007/s10803-006-0327-3

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: Guilford Press.

Brown, E. C., Aman, M. G., & Havercamp, S. M. (2002). Factor analysis and norms for parent ratings on the Aberrant Behavior Checklist-Community for young people in special education. *Research in Developmental Disabilities, 23*(1), 45-60. doi:10.1016/S0891-4222(01)00091-9

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Newbury Park, CA: Sage Publications, Inc.

Byrne, M. B. (2012). *Structural equation modeling with Mplus: Basic concepts, applications, and programming.* New York, NY: Taylor & Francis Group.

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research, 1*(2), 245-276. doi:10.1207/s15327906mbr0102_10

Chebli, S. S., Martin, V., & Lanovaz, M. J. (2016). Prevalence of stereotypy in individuals with developmental disabilities: A systematic review. *Review of Journal of Autism and Developmental Disorders, 3*(2), 107-118. doi:10.1007/s40489-016-0069-x

Church, A. T., & Burke, P. J. (1994). Exploratory and confirmatory tests of the big five and Tellegen's three-and four-dimensional models. *Journal of Personality and Social Psychology, 66*(1), 93-114. doi:10.1037/0022-3514.66.1.93

Cohen, I. L., & Sudhalter, V. S. (2005). *Pervasive Developmental Disorder Behavior Inventory*. Lutz, FL: Psychological Assessment Resources.

Constantino, J. N., & Gruber, C. P. (2012). *Social Responsiveness Scale* (2nd ed.). Los Angeles, CA: Western Psychological Services.

Courtney, M. G. R. (2013). Determining the number of factors to retain in EFA: Using the SPSS R-menu v2.0 to make more judicious estimations. *Practical Assessment, Research & Evaluation, 18*(8), 1-14. Retrieved from http://pareonline.net/getvn.asp?v=18&n=8

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *16*(3), 297-334. doi:10.1007/BF02310555

Cunningham A. B., & Schreibman, L. (2008). Stereotypy in autism: The importance of function. *Research in Autism Spectrum Disorders, 2*(3), 469-479. doi:10.1016/j.rasd.2007.09.006

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonormality and specification error in confirmatory factor analysis. *Psychological Methods, 1*(1), 16-29. doi:10.1037/1082-989X.1.1.16

Davis, N. O., & Carter, A. S. (2014). Social development in autism. In F. R. Volkmar, S. J. Rogers, R. Paul, & K. A. Pelphrey (Eds.), *Handbook of autism and pervasive developmental disorders: Diagnosis, development, and brain mechanisms* (4th ed., Vol 1., pp. 212-229). Hoboken, NJ: Wiley & Sons, Inc.

Davis, N. O., & Kollins, S. H. (2012). Treatment for co-occurring attention deficit/hyperactivity disorder and autism spectrum disorder. *Neurotherapeutics, 9*(3), 518-530. doi:10.1007/s13311-012-0126-9

Diedenhofen, B., & Musch, J. (2015). Cocor: A comprehensive solution for the statistical comparison of correlations. *PLoS ONE, 10*(4), 1-12. doi:10.1371/journal.pone.0121945

DiStefano, C., & Morgan G. B. (2014). A comparison of diagonal weighted least squares robust estimation techniques for ordinal data. *Structural Equation Modeling: A Multidisciplinary Journal, 21*(3), 425-438. doi:10.1080/10705511.2014.915373

Dua, E. H. (2014). *Exploratory factor analysis of the Gilliam Autism Rating Scale—Second Edition with a sample of students with autism spectrum disorders* (Doctoral dissertation). Available from ProQuest Dissertations and Theses Global database. (UMI No. 3629713)

Dunn, O. J., & Clark, V. A. (1969). Correlations measures on the same individuals. *Journal of the American Statistical Association, 64*, 366-377. doi:10.1080/01621459.1969.10500981

Esbensen, A. J., Seltzer, M. M., Lam, K. S., & Bodfish, J. W. (2009). Age-related differences in restricted repetitive behaviors in autism spectrum disorders. *Journal of Autism and Developmental Disorders, 39*(1), 57-66. doi:10.1007/s10803-008-0599-x

Elliott, C. D. (1990). *Differential Ability Scales.* San Antonio, TX: The Psychological Corporation.

Elliott, C. D. (2007). *Differential Ability Scales, Second Edition*. San Antonio, TX: Harcourt Assessment.

Fabrigar, L. R., & Wegener, D. T. (2012). *Exploratory factor analysis*. New York, NY: Oxford University Press.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272-299. doi:10.1037/1082-989X.4.3.272

Falkmer, T., Anderson, K., Falkmer, M., & Horlin, C. (2013). Diagnostic procedures in autism spectrum disorders: A systematic literature review. *European Child & Adolescent Psychiatry, 22*(6), 329-340. doi:10.1007/s00787-013-0375-0

Faul, F., Erdfelder, E., Buchner, A., & Lang, A-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149-1160. doi:10.3758/BRM.41.4.1149

Fisher, R. A. (1925). Statistical methods for research workers. Edinburgh, Scotland: Oliver & Boyd. Retrieved from http://psychclassics.yorku.ca/Fisher/Methods/

Floyd, F. J., & Widaman, K. F. (1995). Factor analysis in the development and refinement of clinical assessment instruments. *Psychological Assessment, 7*(3), 286-299. doi:10.1037/1040-3590.7.3.286

Freund, L. S., & Reiss, A. L. (1991). Rating problem behaviors in outpatients with mental retardation: Use of the Aberrant Behavior Checklist. *Research in Developmental Disabilities, 12*(4), 435-51. doi:10.1016/0891-4222(91)900037-S

Frazier, T. W., Youngstrom, E. A., Speer, L., Embacher, R., Law, P., Constantino, J. . . . Eng, C. (2012). Validation of proposed DSM-5 criteria for autism spectrum disorder. *Journal of the American Academy of Child & Adolescent Psychiatry, 51*(1), 28-40.e3. doi:10.1016/j.jaac.2011.09.021

Gadermann, A. M., Guhn, M., & Zumbo, B. D. (2012). Estimating ordinal reliability for Likert-type and ordinal item response data: A conceptual, empirical, and practical guide. *Practical Assessment, Research & Evaluation, 17*(3), Retrieved from http://pareonline.net/getvn.asp?v=17&n=3

Gerbing, D. W., & Hamilton, J. G. (1996). Viability of exploratory factor analysis as a precursor to confirmatory factor analysis. *Structural Equation Modeling, 3*(1), 62-72. doi:10.1080/10705519609540030

Gilliam, J. E. (1995). *Gilliam Autism Rating Scale—Summary response form*. Austin, TX: Pro-Ed.

Gilliam, J. E. (2006). *Gilliam Autism Rating Scale—Second edition: Examiner's manual.* Austin, TX: Pro-Ed

Glorfield, L. W. (1995). An improvement on Horn's parallel analysis methodology for selecting the correct number of factors to retain. *Educational and Psychological Measurement, 55*(3), 377-393. doi:10.1177/0013164495055003002

Goldman, S., Wang, C., Salgado, M. W., Greene, P. E., Kim, M., & Rapin, I. (2009). Motor stereotypies in children with autism and other developmental disorders. *Developmental Medicine & Child Neurology, 51*(1), 30-38. doi:10.1111/j.1469-8749.2008.03178.x

Gorsuch, R. L. (1997). Exploratory factor analysis: It's role in item analysis. *Journal of Personality Assessment, 68*(3), 532-560. doi:10.1207/s15327752jpa6803_5

Guttman, L. (1954). Some necessary conditions for common factor analysis. *Psychometrika, 19*, 149-161.

Hammill, D. D., Pearson, N. A., & Wiederholt, J. L. (1996). *Comprehensive Test of Nonverbal Intelligence.* Austin, TX: Pro-Ed.

Hampton, J., & Strand, P. S. (2015). A review of level 2 parent-report instruments used to screen children aged 1.5-5 for autism: A meta-analytic update. *Journal of Autism and Developmental Disorders, 45*(8), 2519-2530. doi:10.1007/s10803-015-2419-4

Happé, F. (2011). Criteria, categories, and continua: Autism and related disorders in DSM-5. *Journal of the American Academy of Child & Adolescent Psychiatry, 50*(6), 540-542. doi:10.1016/j.jaac.2011.03.015

Harrington, D. (2009). *Confirmatory factor analysis.* New York, NY: Oxford University Press.

Harwell, M., & LeBeau, B. (2010). Student eligibility for a free lunch as an SES measure in education research. *Educational Researcher, 39*(2), 120-131. doi:10.3102/0013189X10362578

Hassiotis, A., Robotham, D., Canagasabey, A., Romeo, R., Langridge, D., Blizard, R., . . . King, M. (2009). Randomized, single-blind, controlled trial of a specialist behavior therapy team for challenging behavior in adults with intellectual disabilities. *The American Journal of Psychiatry, 166*(11), 1278-1285. doi:10.1176/appi.ajp.2009.08111747

Hayton, J. C., Allen, D. G., & Scarpello, V. (2004). Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. *Methodological Resources, 7*(2), 191-205. doi:10.1177/1094428104263675

Holgado-Tello, P., Chacón-Moscoso, S., Barbero-García, I. & Vila-Abad, E. (2010). Polychoric versus Pearson correlations in exploratory and confirmatory factor analysis of ordinal variables. *Quality & Quantity, 44*(1), 153-166. doi:10.1007/s11135-008-9190-y

Horn, J. L (1965). A rationale and test for the numbers of factors in factor analysis. *Psychometrika, 30*(2), 179-185. doi:10.1007/BF02289447

Hu, L-t, & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. doi:10.1080/10705519909540118

Huerta, M., Bishop, S. L., Duncan, A., Hus, V., & Lord, C. (2012). Application of DSM-5 criteria for autism spectrum disorder to three samples of children with DSM-IV diagnoses of pervasive developmental disorders. *American Journal of Psychiatry, 169*(10), 1056-1064. doi:10.1176/appi.ajp.2012.12020276

Huerta, M., & Lord, C. (2012). Diagnostic evaluation of autism spectrum disorders. *Pediatric Clinics of North America, 59*(1), 103-111. doi:10.1016/j.pcl.2011.10.018

Iacobucci, D. (2010). Structural equations modeling: Fit indices, sample size, and advanced topics. *Journal of Consumer Psychology, 20*(1), 90-98. doi:10.1016/j.jcps.2009.09.003

IBM Corp. (2017). *IBM SPSS Statistics for Macintosh, Version 25*. Armonk, NY: IBM Corp.

Individuals with Disabilities Education Act, 20 U.S.C. § 1400 (2004)

Jackson, D. L., Gillaspy, J. A., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: An overview and some recommendations. *Psychological Methods, 14*(1), 6-23. doi:10.1037/a0014694

Jennrich, R. I., & Sampson, P. F. (1966). Rotation for simple loadings. *Psychotemtrika, 31*(3), 313-323. doi:10.1007/BF02289465

Kaat, A. J., Lecavalier, L., & Aman, M. G. (2014). Validity of the Aberrant Behavior Checklist in children with autism spectrum disorder. *Journal of Autism and Developmental Disorders, 44*(5), 1103-1116. doi:10.1007/s10803-013-1970-0

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika, 23*(3), 187-200. doi:10.1007/BF02289233

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement, 20*(1), 141-151. doi:10.1177/001316446002000116

Kaiser, H. F. (1970). A second generation little jiffy. *Psychometrika, 35*(4), 401-415. doi:10.1007/BF02291817

Kaiser, H. F., & Rice, J. (1974) Little jiffy, mark iv. *Educational and Psychological Measurement, 34*(1), 111-117. doi:10.1177/001316447403400115

Kanner, L. (1943). Autistic disturbances of affective contact. *Nervous Child, 2*, 217-250.

Kaufman, A. S., & Kaufman, N. L. (1983). *Kaufman Assessment Battery for Children*. Circle Pines, MN: American Guidance Service.

Kaufman, A. S., & Kaufman, N. L. (1990). *Kaufman Brief Intelligence Test.* Circle Pines, MN: American Guidance Service, Inc.

Kazdin, A. E. (2017). *Research design in clinical psychology* (5th ed.). [Kindle Edition] Retrieved from Amazon.com

Lai, M. C., Lombardo, M. V., Chakrabarti, B., & Baron-Cohen, S. (2013). Subgrouping the autism "spectrum": reflections on DSM-5. *PLoS Biology, 11*(4), e1001544. doi:10.1371/journal.pbio.1001544

Lam, K. D. (2005). Alternative method for scoring Repetitive Behavior Scale—Revised version. Retrieved from https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0ahUKEwj2iPmOsrPYAhVM6oMKHYojCjYQFgguMAA&url=https%3A%2F%2Fpsychmed.osu.edu%2Fwp-content%2Fuploads%2F2017%2F04%2FRBS-R-Lam-Scoring-Supplement2-1.doc&usg=AOvVaw3nL2_Z55uORbPHphN3mjY7

Lam, K. D. (2004). *The Repetitive Behavior Scale-Revised: Independent validation and the effects of subject variables* (Doctoral dissertation). Available from ProQuest Dissertations and Theses Global database. (UMI No. 3148184)

Lam, K. S., & Aman, M. G. (2007). The Repetitive Behavior Scale-Revised: Independent validation in individuals with autism spectrum disorders. *Journal of Autism and Developmental Disorders, 37*(5), 855-866. doi:10.1007/s10803-006-0213-z

Lavelle, T. A., Weinstein, M. C., Newhouse, J. P., Munir, K., Kuhlthau, K. A., & Prosser, L. A. (2014). Economic burden of childhood autism spectrum disorders. *Pediatrics, 133*(3), e520-e529. doi:10.1542/peds.2013-0763

Lecavalier, L. (2005). An evaluation of the Gilliam Autism Rating Scale. *Journal of Autism and Developmental Disorders, 35*(6), 795-805. doi:10.1007/s10803-005-0025-6

Lecavalier, L. (2013). Thoughts on the DSM-5. *Autism, 17*(5), 507-509. doi:10.1177/1362361313500865

LeCouteur, A., Lord, C., & Rutter, M. (2003). *The Autism Diagnostic Interview: Revised* (ADI-R). Los Angeles, CA: Western Psychological Services.

Leigh, J. P., & Du, J. (2015). Brief report: Forecasting the economic burden of autism in 2015 and 2025 in the United States. *Journal of Autism and Developmental Disorders, 45*(12), 4135-4139. doi:10.1007/s10803-015-2521-7

Lehotkay, R., Devi, T. S., Raju, M. V. R., Bada, P. K., Nuti., S., Kempf, N., & Carminati, G. G. (2015). Factor validity and reliability of the Aberrant Behavior Checklist-Community (ABC-C) in an Indian population with intellectual disability. *Journal of Intellectual Disability Research, 59*(3), 208-214. doi:10.1111/jir.12128

Li, C. H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods, 48*(3), 936-949. doi:10.3758/s13428-015-0619-7

Loebel, A., Brams, M., Goldman, R. S., Silva, R., Hernandez, D., Deng, L., . . . Findling, R. L. (2016). Lurasidone for the treatment of irritability associated with autistic disorder. *Journal of Autism and Developmental Disorders, 46*(4), 1153-1163. doi:10.1007/s10803-015-2628-x

Long, J. S. (1983). *Confirmatory factor analysis: A preface to Liseral.* Newbury Park, CA: Sage Publications, Inc.

Lord, C., Corsello, C., & Grzadzinski, R. (2014). Diagnostic instruments in autistic spectrum disorders. In F. R. Volkmar, S. J. Rogers, R. Paul, & K. A. Pelphrey (Eds.), *Handbook of autism and pervasive developmental disorders: Assessment, interventions, and policy* (4th ed., Vol 2, pp. 609-660). Hoboken, NJ: Wiley & Sons, Inc.

Lord, C., & Jones, R. M. (2012). Annual research review: Re-thinking the classification of autism spectrum disorders. *Journal of Child Psychology and Psychiatry, 53*(5), 490-509. doi:10.1111/j.1469-7610.2012.02547.x

Lord, C., Petkova, E., Hus, V., Gan, W., Lu, F., Martin, D. M. . . . Risi, S. (2012). A multisite study of the clinical diagnosis of different Autism spectrum disorders. *Archives of General Psychiatry, 69*(3), 306-313. doi:10.1001/archgenpsychiatry.2011.148

Lord, C., Rutter, M., DiLavore, P. C., & Risi, S. (2000). *Autism diagnostic observation schedule (ADOS)*. Los Angeles: Western Psychological Services.

Lord, C., Rutter, M., DiLavore, P. C., Risi, S., Gotham, K., & Bishop, S. (2012). *Autism diagnostic observation schedule, second edition (ADOS-2)*. Los Angeles: Western Psychological Services.

Lord, C., Wagner, A., Rogers, S., Szatmari, P., Aman, M., Charman, T., . . . Yoder, P. (2005).

Challenges in evaluating psychosocial interventions for autistic spectrum disorders. *Journal of Autism and Developmental Disorders, 35*(6), 695-708. doi:10.1007/s10803-005-0017-6

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130-149. doi:10.1037/1082-989X.1.2.130

MacCallum, R. C., Widaman, K., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *Psychological Methods,* 4(1), 84-99. doi:10.1037/1082-989X.4.1.84

MacDonald, R., Green, G., Mansfield, R., Geckeler, A., Gardenier, N., Anderson, J., . . . Sanchez, J. (2007). Stereotypy in young children with autism and typically developing children. *Research in Developmental Disabilities, 28*(3), 266-277. doi:10.1016/j.ridd.2006.01.004

Magnuson, K. M., & Constantino, J. N. (2011). *Journal of Developmental and Behavioral Pediatrics, 32*(4), 332-340. doi:10.1097/DBP.0b013e318213f56c

Mahatmya, D., Zobel, A., & Valdovinos, M. G. (2008). Treatment approaches for self-injurious behavior in individuals with autism: Behavioral and pharmacological methods. *Journal of Early and Intensive Behavior Intervention, 5*(1), 106-118. doi:10.1037/h0100413

Mandy, W., Roughan, L. & Skuse, D. (2014). Three dimensions of oppositionality in autism spectrum disorder. *Journal of Abnormal Child Psychology, 42*(2), 291-300. doi:10.1007/s10802-013-9778-0

Mannion, A., & Leader, G. (2014). Attention-deficit/hyperactivity disorder (AD/HD) in autism spectrum disorder. *Research in Autism Spectrum Disorders, 8*(4), 432-439. doi:10.1016/j.rasd.2013.12.021

Marcus, R. N., Owen, R., Kamen, L., Manos, G., McQuade, R. D., Carson, W. H., & Aman, M. G. (2009). A placebo-controlled, fixed-dose study of aripiprazole in children and adolescents with irritability associated with autistic disorder. *Journal of the American Academy of Child and Adolescent Psychiatry, 48*(11), 1110-1119. doi:10.1097/CHI.0b013e3181b76658

Marshburn, E. C., & Aman, M .G. (1992). Factor validity and norms for the Aberrant Behavior Checklist in a community sample of children with mental retardation. *Journal of Autism and Developmental Disorders, 22*(3), 357-373. doi:10.1007/BF01048240

Masi, A., DeMayo, M. M., Glozier, N., & Guastella A. J. (2017). An overview of autism spectrum disorder, heterogeneity and treatment options. *Neuroscience Bulletin, 33*(2), 183-193. doi:10.1007/s12264-017-0100-y

Matson, J. L. (2009). Aggression and tantrums in children with autism: A review of behavioral

treatments and maintaining variables. *Journal of Mental Health Research in Intellectual Disabilities, 2*(3), 169-187. doi:10.1080/19315860902725875

Matson, J. L., Beighley, J., & Turygin, N. (2012). Autism diagnosis and screening: Factors to consider in differential diagnosis. *Research in Autism Spectrum Disorders, 6*(1), 19-24. doi:10.1016/j.rasd.2011.08.003

Matson, J. L., & LoVullo, S. V. (2008). A review of behavioral treatments for self-injurious behaviors of persons with autism spectrum disorders. *Behavior Modification, 32*(1), 61-76. doi:10.1177/0145445507304581

Matson, J. L., Rieske, R. D., & Williams, L. W. (2013). The relationship between autism spectrum disorders and attention-deficit/hyperactivity disorder: An overview. *Research in Developmental Disabilities, 34*(9), 2475-2484. doi:10.1016/j.ridd.2013.05.021

Matson, J. L., Wilkins, J., & Macken, J. (2008). The relationship of challenging behaviors to severity and symptoms of autism spectrum disorders. *Journal of Mental Health Research in Intellectual Disabilities, 2*(1), 29-44. doi:10.1080/19315860802611415

Mayes, S. D., & Calhoun, S. L. (2011). Impact of IQ, age, SES, gender, and race on autistic symptoms. *Research in Autism Spectrum Disorders, 5*(2), 749-757. doi:10.1016/j.rasd.2010.09.002

Mazefsky, C. A., McPartland, J. C., Gastgeb, H. Z., & Minshew, N. J. (2013). Brief report: Comparability of DSM-IV and DSM-5 ASD research samples. *Journal of Autism Developmental Disorders, 43*(5), 1236-1242. doi:10.1007/s10803-012-1665-y

McCarthy, D. (1972). *Manual for the McCarthy Scales of Children's Abilities*. New York, NY: The Psychological Corporation.

McConachie, H., Parr, J. R., Glod, M., Hanratty, J., Livingstone, N., Oono, I. P., . . . Williams, K. (2015). Systematic review of tools to measure outcomes for young children with autism spectrum disorder. *Health Technology Assessment, 19*(41), 1-538. doi:10.3310/hta19410

McCracken, J. T., McGough, J., Shah, B., Cronin, P., Hong, D., Aman, M. G., . . . McMahon, D. (2002). Risperidone in children with autism and serious behavioral problems. *The New England Journal of Medicine, 347*(5), 314-321. doi:10.1056/NEJMoa013171

McPartland, J. C., Reichow, B., & Volkmar, F. R. (2012). Sensitivity and specificity of proposed DSM-5 diagnostic criteria for autism spectrum disorder. *Journal of the American Academy of Child and Adolescent Psychiatry, 51*(4), 368-383. doi:10.1016/j.jaac.2012.01.007

Merrell, K. W. (2001). Assessment of children's social skills: Recent developments, best practices, and new directions. *Exceptionality, 9*(1-2), 3-18.

doi:10.1080/09362835.2001.9666988

Mikita, N., Hollocks, M. J., Papadopoulos, A. S., Aslani, A., Harrison, S., Leibenluft, E., . . . Stringaris, A. (2015). Irritability in boys with autism spectrum disorders: An investigation of physiological reactivity. *Journal of Child Psychology and Psychiatry, 56*(10), 1118-1126. doi:10.1111/jcpp.12382

Miller, M. L., Fee, V. E., & Netterville, A. K. (2004). Psychometric properties of ADHD rating scales among children with mental retardation I: Reliability. *Research in Developmental Disabilities, 25*(5), 459-476. doi:10.1016/j.ridd.2003.11.003

Minshawi, N. F., Hurwitz, S., Fodstad, J. C., Biebl, S., Morriss, D. H., & McDougle, C. J. (2014). The association between self-injurious behaviors and autism spectrum disorders. *Psychology Research and Behavior Management, 7,* 125-136. doi:10.2147/PRBM.S44635

Mire, S. S., Nowell, K. P., Kubiszyn, T., & Goin-Kochel, R. P. (2014). Psychotropic medication use among children with autism spectrum disorders within the Simons Simplex Collection: Are core features of autism spectrum disorder related? *Autism, 18*(8), 933-942. doi:10.1177/1362361313498518

Mirenda, P., Smith, I. M., Vaillancourt, T., Georgiades, S., Duku, E., Szatmari, P., . . . Zwaigenbaum, L. (2010). Validating the Repetitive Behavior Scale-Revised in young children with autism spectrum disorder. *Journal of Autism and Developmental Disorders, 40*(12), 1521-1530. doi:10.1007/s10803-010-1012-0

Mirwis, J. E. (2011). *Exploratory factor analysis of the Aberrant Behavior Checklist—Community (ABC-C) with a sample of individuals with autism spectrum disorders* (Doctoral dissertation). Available from ProQuest Dissertations and Theses Global database. (UMI No. 3460858)

Muthén, B. O. (1993). Goodness of Fit with Categorical and Other Non-Normal Variables. In K. A. Bollen, & J. S. Long (Eds.), Testing Structural Equation Models (pp. 205-243). Newbury Park, CA: Sage Publications.

Muthén, B. O., du Toit, S. H. C., & Spisic, D. (1997). Robust inference using weighted least squares and quadratic estimating equations in latent variable modeling with categorical and continuous outcomes. Retrieved from https://www.statmodel.com/download/Article_075.pdf

Muthén, L. K., & Muthén, B. O. (2002). How to use a monte carlo study to decide on sample size and determine power. *Structural Equation Modeling: A Multidisciplinary Journal, 9*(4), 599-620. doi:10.1207/S15328007SEM0904_8

Muthén, L. K., & Muthén, B. O. (1998-2017). *Mplus user's guide* (8th ed.). Los Angeles, CA: Muthén & Muthén

Naglieri, J. A., Das, J. P., & Goldstein, S. (2014). *Cognitive Assessment System-Second Edition (2nd ed.).* Austin, TX: Pro-Ed.

Nehring, A. D., Nehring, E. F., Bruni, J. R., & Randolph, P. L. (1992). *Learning Accomplishment Profile—Diagnostic Standardized Assessment*. Lewisville, NC: Kaplan Press.

Nelson, A. T. (2015). *Exploratory factor analysis of the social responsiveness scale—second edition in a sample of individuals with autism spectrum disorders* (Doctoral dissertation). Available from ProQuest Dissertations and Theses Global database. (UMI No. 3714653)

Neuhaus, J. O., Wrigley, C. (1954). The quartimax method: An analytic approach to orthogonal simple structure. *The British Journal of Statistical Psychology, 7*(2), 81-91. doi:10.1111/j.2044-8317.1954.tb00147.x

Newton, J. T., & Sturmey, P. (1988). The Aberrant Behavior Checklist: A British replication and extension of its psychometric properties. *Journal of Mental Deficiency Research, 32*(2), 87-92. doi:10.1111/j.1365-2788.1988.tb01394.x

Nicholson, L.M., Slater, S. J., Chriqui, J. F., Chaloupka, F. (2014). Validating adolescent socioeconomic status: Comparing school free and reduced price lunch with community measures. *Spatial Demography, 2*(1), 55-65. doi:10.1007/BF03354904

Norris, M., & Lecavalier, L. (2010b). Evaluating the use of exploratory factor analysis in developmental disability psychological research. *Journal of Autism and Developmental Disorders, 40*(1), 8-20. doi:10.1007/s10803-009-0816-2.

Norris, M., & Lecavalier, L. (2010a). Screening accuracy of level 2 autism spectrum disorder rating scales. *Autism, 14*(4), 263-284. doi:10.1177/1362361309348071

Norris, M., Lecavalier, L., & Edwards, M. C. (2012). The structure of autism symptoms as measured by the Autism diagnostic observation schedule. *Journal of Autism and Developmental Disorders, 42*(6), 1075-1086. doi:10.1007/s10803-011-1348-0

Nunnally, J. (1978). *Psychometric theory* (2nd ed.). New York: McGraw-Hill.

Oliver, C., & Richards, C. (2015). Practitioner review: Self-injurious behaviour in children with developmental delay. *Journal of Child Psychology and Psychiatry, 56*(10), 1042-1054. doi:10.1111/jcpp.12425

O'Nions, E., Vidling, E., Floyd, C., Quinlan, E., Pidgeon, C., Gould, J., & Happé, F. (2018). Dimensions of difficulty with children reported to have an autism spectrum diagnosis and features of extreme/'pathological' demand avoidance. *Child and Adolescent Mental Health, 23*(3), 220-227. doi:10.1111/camh.12242

Ono, Y. (1996). Factor validity and reliability for the Aberrant Behavior Checklist-Community in a Japanese population with mental retardation. *Research in Developmental Disabilities, 17*(4), 303-309. doi:10.1016/0891-4222(96)00015-7

O'Rourke, N. & Hatcher, L. (2013). *A step-by-step approach to using SAS for factor analysis and structural equation modeling* (2nd ed.). Cary, NC: SAS Institute Inc.

Osborne, J. W. (2014). *Best practices in exploratory factor analysis*. Retrieved from https://www.researchgate.net/publication/265248967_Best_Practices_in_Exploratory_Factor_Analysis

Osborne, J. W. (2015). What is rotating in exploratory factor analysis? *Practical Assessment, Research & Evaluation,* 20(2), 1-7. Retrieved from http://pareonline.net/getvn.asp?v=20&n=2

Osborne, J. W., & Banjanovic, E. S. (2016). *Exploratory factor analysis with SAS*. Cary, NC: SAS Institute Inc.

Osborne, J. W., & Costello, A. B. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation, 10*(7), 1-9. Retrieved from http://pareonline.net/getvn.asp?v=10&n=7

Ozonoff, S., Goodlin-Jones, B. L., & Solomon, M. (2005). Evidence-based assessment of autism spectrum disorders in children and adolescents. *Journal of Clinical Child and Adolescent Psychology, 34*(3), 523-540. doi:10.1207/s15374424jccp3403_8

Pearson, K. (1900). Mathematical contributions to the theory of evolution. VII. On the correlation of characters not quantitatively measurable. *Philosophical Transactions of the Royal Society of London. Series A., Containing Papers of a Mathematical or Physical Character, 195,* 1-47+405. doi:10.1098/rsta.1900.0022

Pedhazur, E. J., & Schemlkin, L. P. (1991). *Measurement, design, and analysis: An integrated approach.* Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Péter, Z., Oliphant, M. E., & Fernandez, T. V. (2017). Motor stereotypies: A pathophysiological review. *Frontiers in Neuroscience, 11*(171), 1-6. doi:10.3389/fnins.2017.00171

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research.* Thousand Oaks, CA: Sage Publications, Inc.

Portney, L. G., & Watkins, M. P. (2000). *Foundations of clinical research: Applications to practice* (2nd ed.) Upper Saddle River, NJ: Prentice Hall Health.

R Core Team (2013). R: A language and environment for statistical computing. R Foundation for

Statistical Computing, Vienna, Austria. Retrieved from http://www.R-project.org/

Reynolds, C. R., & Kamphaus, R. W. (1992) Behavior Assessment System for Children. Circle Pines, MN: American Guidance Service.

Reynolds, C. R., & Kamphaus, R. W. (2015). *BASC-3: Behavior Assessment System for Children* (3rd ed.). Bloomington, MN: NCS Pearson, Inc.

Ripamonti, L. (2016). Disability, diversity, and autism: Philosophical perspectives on health. *The New Bioethics, 22*(1), 56-70. doi:10.1080/20502877.2016.1151256

Roid, G. H. (2003). *Stanford-Binet Intelligence Scales, Fifth Edition (SB:5)*. Itasca, IL: Riverside Publishing.

Rojahn, J., & Helsel, W. J. (1991). The Aberrant Behavior Checklist in children and adolescents with dual diagnosis. *Journal of Autism and Developmental Disorders, 21*(1), 17-28. doi:10.1007/BF02206994

Rojahn, J., Schroeder, S. R., Mayo-Ortega, L., Oyama-Ganiko, R., LeBlanc, J., Marquis, J., & Berke, E. (2013). Validity and reliability of the Behavior Problems Inventory, the Aberrant Behavior Checklist, and the Repetitive Behavior Scale—Revised among infants and toddlers at risk for intellectual or developmental disabilities: A multi-method assessment approach. *Research in Developmental Disabilities, 34*(5), 1804-1814. doi:10.1016/j.ridd.2013.02.024

Sansone, S. M., Widaman, K. F., Hall, S. S., Reiss, A. L., Lightbody, A., Kaufmann, W. E., . . . Hessl, D. (2012). Psychometric study of the Aberrant Behavior Checklist in fragile x syndrome and implications for targeted treatment. *Journal of Autism and Developmental Disorders, 42*(7), 1377-1392. doi:10.1007/s10803-011-1370-2

SAS Institute, Inc. (2013). *SAS version 9.4*. Cary, NC: SAS Institute Inc.

Satorra, A., & Bentler, P. M. (2001). Scaled difference chi-square test statistic for moment structure analysis. *Psychometrika, 66*(4), 507-514. doi:10.1007/BF02296192

Satorra, A., & Bentler, P. M. (2010). Ensuring positiveness of the scaled difference chi-square test statistic. *Psychometrika, 75*(2), 243-248. doi:10.1007/s11336-009-9135-y

Sattler, J. M. (2008) *Assessment of children: Cognitive foundations* (5th ed.). La Mesa, CA: Jerome M. Sattler, Publisher, Inc.

Schopler, E. S., Reichler, R. J., & Renner, B. R. (1986). *The Childhood Autism Rating Scale (CARS) for diagnostic screening and classification of autism*. Irvington, NY: Irvington.

Schmidt, J. D., Huete, J. M., Fodstad, J. C., Chin, M. D., & Kurtz, P. F. (2013). An evaluation of

the Aberrant Behavior Checklist for children under age 5. *Research in Developmental Disabilities, 34*(4), 1190-1197. doi:10.1016/j.ridd.2013.01.002

Schmitt, T. A., & Sass, D. A. (2011). Rotation criteria and hypothesis testing for exploratory factor analysis: Implications for factor pattern loadings and interfactor correlations. *Educational and Psychological Measurement, 71*(1), 95-113. doi:10.1177/0013164410387348

Schroeder, S. R., Rojahn, J., & Reese, R. M. (1997). Brief report: Reliability and validity of instruments for assessing psychotropic medication effects on self-injurious behavior in mental retardation. *Journal of Autism and Developmental Disorders, 27*(1), 89-102. doi:10.1023/A:10258253

Snyder, T. & Musu-Gillette, L. (2015, April 16). Free or reduced price lunch: A proxy for poverty [Web log comment]. Retrieved from https://nces.ed.gov/blogs/nces/post/free-or-reduced-price-lunch-a-proxy-for-poverty

Sparrow, S. S., Cicchetti, D. V., & Balla, D. A. (2005) *Vineland adaptive behavior scales: Second edition (VABS-II), survey, interview form/caregiver rating form*. Livonia, MN: Pearson Assessments.

Sprenger, L., Bühler, E., Poustka, L., Bach, C., Heinzel-Gutenbrunner, M. Kamp-Becker, I., & Bachmann, C. (2013). Impact of ADHD symptoms on autism spectrum disorder symptom severity. *Research in Developmental Disabilities, 34*(10), 3545-3552. doi:10.1016/j.ridd.2013.07.028

Simonoff, E., Jones, C. R. G., Pickles, A., Happé, F., Baird, G., Charman, T. (2012). Severe mood problems in adolescents with autism spectrum disorder. *The Journal of Child Psychology and Psychiatry, 53*(11), 1157-1166. doi:10.1111/j.1469-7610.2012.02600.x

Soke, G. N., Rosenberg, S. A., Hamman, R. F., Fingerlin, T., Robinson, C., Carpenter, L., . . . DiGuiseppi, C. (2016). Brief report: Prevalence of self-injurious behaviors among children with autism spectrum disorder-a population-based study. *Journal of Autism and Developmental Disorders, 46*(11), 3607-3614. doi:10.1007/s10803-016-2879-1

Sörbom, D. (1989). Model modification. *Psychometrika, 54*(3), 371-384. doi: 10.1007/BF02294623

Stachnik, J., & Gabay, M. (2010). Emerging role of aripiprazole for treatment of irritability associated with autistic disorder in children and adolescents. *Adolescent Health, Medicine and Therapeutics, 1, 104-114.* doi:10.2147/AHMT.S9819

Steiger, J. H. (2016). Notes on the Steiger-Lind (1980) handout. *Structural Equation Modeling: A Multidisciplinary Journal, 23*(6), 777-781. doi:10.1080/10705511.2016.1217487

Stringaris, A. (2011). Irritability in children and adolescents: a challenge for DSM-5. *European*

Child and Adolescent Psychiatry, 20(2), 61-66. doi:10.1007/s00787-010-0150-4

Thorndike, R. L., Hagen, E. P., & Sattler, J. M. (1986). *The Stanford-Binet Intelligence Scale: Fourth Edition, Guide for administering and scoring (2nd printing).* Chicago, IL: Riverside Publishing.

Trammell, B., Wilczynski, S. M., Dale, B., & McIntosh, D. E. (2013). Assessment and differential diagnosis of comorbid conditions in adolescents and adults with autism spectrum disorders. *Psychology in the Schools, 50*(9), 936-946. doi:10.1002/pits.21720

Turner-Brown, L. M., Lam, K. S. L., Holtzclaw, T. N., Dichter, G. S., & Bodfish, J. W. (2011). Phenomenology and measurement of circumscribed interests in autism spectrum disorders. *Autism, 15*(4), 437-456. doi:10.1177/1362361310386507

Urbina, S. (2014). *Essentials of psychological* testing (2nd ed.). Hoboken, NJ: John Wiley & Sons, Inc.

Velicer, W. F. (1976). Determining the number of components from the matrix of partial correlations. *Psychometrika, 41*(3), 321-327. doi:10.1007/BF02293557

Velicer, W. F., Eaton, C. A., & Fava, J. L. (2000). Construct explication through factor or component analysis: A review and evaluation of alternative procedures for determining the number of factors or components. In R. D. Goffin & E, Helmes (Eds.). *Problems and solutions in human assessment: Honoring Douglas Jackson at seventy* (pp. 41-71). Boston, MA: Kluwer Academic Publishers.

Volker, M. A. (2012). Introduction to the special issue: High-functioning autism spectrum disorders in the schools. *Psychology in the Schools, 49*(10), 911-916. doi:10.1002/pits.21653

Volker, M. A., Dua, E. H., Lopata, C., Thomeer, M . L., Toomey, J. A., Smerbeck, A. M., . . . Lee, G. K. (2016). Factor structure, internal consistency, and screening sensitivity of the GARS-2 in a developmental disabilities sample. *Autism Research and Treatment, 2016*, 1-12. doi:10.1155/2016/8243079

Volker, M. A., Thomeer, M. L., & Lopata, C. (2010). Pervasive developmental disorders. In A. S. Davis (Ed.), *Handbook of pediatric neuropsychology* (pp. 501-535). New York, NY: Spring Publishing Company, LLC

Volkmar, F. R., Reichow, B., Westphal, A., & Mandell, D. S. (2014). Autism and the autism spectrum: Diagnostic concepts. In F. R. Volkmar, S. J. Rogers, R. Paul, & K. A. Pelphrey (Eds.). *Handbook of autism and pervasive developmental disorders: Diagnosis, development, and brain mechanisms* (4th ed., Vol 1, pp. 3-28). Hoboken, NJ: Wiley & Sons, Inc.

Wechsler, D. (1974). *Wechsler Intelligence Scale for Children-Revised.* New York, NY: The

Psychological Corporation.

Wechsler, D. (1989). *The Wechsler Preschool and Primary Scale of Intelligence-Revised.* San Antonio, TX: The Psychological Corporation.

Wechsler, D. (1991). *The Wechsler Intelligence Scale for Children-Third Edition*. San Antonio, TX: The Psychological Corporation.

Wechsler, D. (1997), *Wechsler Adult Intelligence Scale-Third Edition (WAIS-III).* San Antonio, TX: The Psychological Corporation.

Wechsler, D. (1999). *Wechsler Abbreviated Scale of Intelligence (WASI).* San Antonio, TX: Psychological Corporation.

Wechsler, D. (2002). *The Wechsler Preschool and Primary Scale of Intelligence-Third Edition.* San Antonio, TX: The Psychological Corporation.

Wechsler, D. (2011). *Wechsler Abbreviated Scale of Intelligence-Second Edition (WASI-II).* San Antonio, TX: NCS Pearson.

Wechsler, D. (2012). *Wechsler Preschool and Primary Scale of Intelligence-Fourth Edition.* San Antonio, TX: The Psychological Corporation.

Wheeler, A., Raspa, M., Bann, C., Bishop, E., Hessl, D. Sacco, P., & Bailey, D. B., Jr. (2014). Anxiety, attention problems, hyperactivity, and the Aberrant Behavior Checklist in fragile x syndrome. *American Journal of Medical Genetics, 164A*(1), 141-155. doi:10.1002/ajmg.a.36232

White, S. W., Keonig, K., & Scahill, L. (2007). Social skills development in children with autism spectrum disorders: A review of the intervention research. *Journal of Autism and Developmental Disorders, 37*(10), 1858-1868. doi:10.1007/s10803-006-0320-x

Witwer, A. N., & Lecavalier, L. (2008). Examining the validity of autism spectrum disorder subtypes. *Journal of Autism and Developmental Disorders, 38*(9), 1611-1624. doi:10.1007/s10803-008-0541-2

Wothke, W. (1993). Nonpositive definite matrices in structural modeling. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 256-293). Newbury Park, CA: Sage Publications, Inc.

Zeilinger, E. L., Weber, G., & Haverman, M. J. (2011). Psychometric properties and norms of the German ABC-Community and PAS-ADD Checklist. *Research in Developmental Disabilities, 32*(6), 2431-2440. doi:10.1016/j.ridd.2011.07.017

Zumbo, B. D., Gadermann, A. M., & Zeisser, C. (2007). Ordinal versions of coefficients alpha

and theta for Likert rating scales. *Journal of Modern Applied Statistical Methods*, *6*(1), 21-29. doi:10.22237/jmasm/1177992180