THE AUTISM SPECTRUM TRAIT SCALE: TESTING PSYCHOMETRIC PROPERTIES

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DEDICATION

I dedicate my thesis to the people I love. Thank you, from the bottom of my heart, for each of your contributions that have shaped my journey and made this thesis possible. It truly takes a village.

To Eliana, meeting you ignited my desire to pursue a career that I am deeply passionate about. Your beautiful mind has illuminated the depth, complexity, and uniqueness that underlies autism. To Eliana's family – Meredith, Lynda, Michael, and Zorina – thank you for teaching me how to foster an incredibly strong bond with a child with autism. You've opened my eyes to a beautiful world that has been an honor to be a part of. To David, Jacob, and Grace, my friends with autism, thank you all for sharing your stories with me and for your invaluable insights into autism in adulthood.

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And to everyone with an invisible neurodifference, I wholeheartedly dedicate this thesis to you. I hope that you have access to the resources and support necessary for you to flourish and grow to your fullest potential. I hope that you embrace yourself and your brain unconditionally, and I stand in solidarity with you.

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ABSTRACT

Autism spectrum condition (ASC) is a neurodevelopmental condition characterized by a spectrum of neuropsychological and behavioral impairments ranging from mild to severe. Formal diagnostic assessments primarily rely on a comprehensive evaluation of behavioral and developmental factors. However, the self-report assessments currently used have limitations which threaten the scales' reliability and validity. The purpose of this study was to develop and assess the psychometric properties of the Autism Spectrum Trait Scale (ASTS), a new self-report scale developed to detect ASC in adults. Exploratory factor analysis (EFA) (n = 764) was conducted to develop the factor structure, and confirmatory factor analysis (CFA) (n = 754) was performed to determine model fit. The results indicated a stable six-factor model with good model fit, metric measurement invariance, and relatively high sensitivity and specificity. These findings provide evidence for the utilization of the ASTS as a component of assessment for ASC in adults.

Keywords: autism spectrum condition, scale development, exploratory factor analysis, confirmatory factor analysis, measurement invariance, sensitivity, specificity.

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CHAPTER I

INTRODUCTION

Background of ASC

Autism spectrum disorder (ASD), now commonly referred to as autism spectrum condition (ASC), is a neurodevelopmental condition characterized by a spectrum of neuropsychological and behavioral impairments ranging from mild to severe (American Psychiatric Association [APA], 2022). ASC encompasses four conditions including autism, Asperger's syndrome, pervasive developmental disorder – not otherwise specified (PDD-NOS), and childhood disintegrative disorder (CDD). The Autism and Developmental Disabilities Monitoring Network (ADDM) reported a growing prevalence of ASC, estimating that 1 in 36 children are affected, and that the prevalence is 3.8 times higher in boys than girls (Maenner et al., 2023). The neurobiological basis of ASC indicates that symptoms emerge during childhood and persist throughout one's entire lifespan. Individuals with ASC often encounter challenges in social and communicative relationships and sensory integration and processing, as well as exhibiting patterns of restricted or repetitive behaviors (Busch, 2020). As a result, these individuals are at an increased risk of experiencing traumatic events such as bullying, feeling misunderstood, and having low self-esteem (Stack & Lucyshyn, 2019). Therefore, receiving the proper

diagnosis is critical for an individual to better understand themselves as well as their symptoms.

Assessment and Diagnosis of ASC

The assessment and diagnosis of autism spectrum condition (ASC) is intricate, and various factors contribute to its complexity. One aspect lies in the relatively unexplored nature of the many facets of this condition (Zhai et al., 2023). For instance, the sensory processing differences among individuals with ASC have been overlooked for many years. These sensory and perceptual differences have a profound impact on the way individuals perceive the world (Busch, 2020). Recent studies elucidated the neurological basis of these processing differences and highlighted the importance of acknowledging their impact (Balasco et al., 2020; Cheung & Lau, 2023; Dakin and Frith, 2018). For example, vagaries of visual perception in individuals with autism may be associated with their challenges in motion processing and social cognition (Dakin and Frith, 2018).

Another contributing factor to the diagnosis and assessment of ASC arises from the previously conflicting diagnostic content between the Diagnostic and Statistical Manual of Mental Disorders (DSM) and the International Classification of Diseases (ICD). Specifically, the inclusion of Asperger's syndrome as part of the ASC diagnosis has evoked controversy among professionals and the public. While some individuals express strong disapproval of this notion (Chambers et al., 2020), others hold the belief that the terms "Asperger's" and "autism" can be used interchangeably (Cascio, 2021). This change has also led to those previously diagnosed with Asperger's syndrome expressing identity confusion as a direct consequence (Topal & Tufan, 2021). Prior to

these discussions and advancements in research, there was limited understanding of ASC. The lack of knowledge posed a particular challenge in the development of diagnostic tools designed to effectively detect this condition (Karmiloff-Smith, 2018).

Limitations in the Assessment and Diagnosis of ASC

Due to the unknown etiological basis of ASC, official diagnostic assessments primarily rely on a comprehensive evaluation of behavioral and developmental factors (Bölte et al., 2019; Thabtah & Peebles, 2019). The intricate nature of this condition justifies that a diagnosis should exclusively be provided by experienced clinicians, using comprehensive clinical information and multiple modes of assessment (Carpenter, 2012). When evaluating children, clinicians commonly use assessments such as the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2) or the Autism Diagnostic Interview-Revised (ADI-R) (Lord et al., 1994). However, obtaining this type of formal diagnosis can be a time-consuming and costly process, especially for individuals who are not able to be assessed until adulthood (Kupper et al., 2020). Similarly, diagnostic tools for the detection of ASC in adults are limited, with the majority of tools primarily focused on diagnosing children (Matson et al., 2007).

The self-report assessments currently used for detecting ASC have limitations which threaten the scales' reliability and validity. These threats to the psychometric properties impact the ability to accurately detect ASC, causing controversy over the effectiveness of the scales (Jia et al., 2021). A few of the well-known self-report measures for detecting ASC include the Systemizing Quotient (SQ; Baron-Cohen et al., 2003), the Adult Repetitive Behaviors Questionnaire-2-Revised (RBQ-2A-R; Barrett et al., 2015), the Autism Spectrum Quotient (AQ; Baron-Cohen et al., 2001), the Ritvo

Autism Asperger Diagnostic Scale-Revised (RAADS-R; Ritvo et al., 2011), and the shortened version of the RAADS-R, the RAADS-14 (Eriksson et al., 2014).

Regardless of their popularity, limitations within each of these scales have been found. A few examples include the AQ and SQ not utilizing modern diagnostic content and containing validity issues, the RAADS-R and RAADS-14 containing subscales which are not consistent with DSM and ICD diagnostic criteria, and the RBQ-2A-R having never been tested via confirmatory factor analysis (CFA) (Jia et al., 2021). Moreover, as the diagnostic criteria only recently recognized atypical sensory processing, multiple scales are missing critical diagnostic content (Barrett et al., 2015; Baron-Cohen, 2001). Various studies discuss the criticality of creating an effective self-report measure to aid in this ongoing dilemma (Filipek et al., 2000; Fleiss, 1986; Guthrie et al., 2012; Kaufman, 2022). Thus, the development of a reliable and valid self-report scale for diagnosing ASC in adults could provide valuable clinical information to use during assessments.

Purpose of the Study

The creation of a diagnostic assessment requires testing numerous psychometric aspects with tedious methodology. Extensive research has highlighted a presence of systematically and psychometrically flawed assessments used in the field of psychology (Al-Dajani et al., 2016; Dunning et al., 2004; Opitz et al., 2020; Strauss et al., 2020). To take these issues into account, the Autism Spectrum Trait Scale (ASTS) was developed as an attempt to overcome the limitations of current diagnostic scales. This was done by (a) integrating modern diagnostic content and adaptive items including sensory processing integration, (b) utilizing recently updated and revised DSM criteria and subscales, (c)

emphasizing reversed questioning to limit the possibility of validity issues and personal bias that may occur while self-reporting symptoms, and (d) efficiently testing the factor structure of this scale to ensure a psychometrically sound self-report instrument. Once the ASTS is finalized, it may aid in the detection and identification of ASC in undiagnosed adults.

CHAPTER II

METHOD

Participants

Recruitment

Participants were recruited through various modes including ResearchMatch, Cleveland State University's (CSU) Sona System portal, and social media (see Appendix B). The majority of participants were obtained via ResearchMatch, a nonprofit program funded by the National Institute of Health created to connect individuals with clinical research studies throughout the United States (Harris et al., 2012). There were no guaranteed direct benefits for participating in this study. However, all volunteers who participated through ResearchMatch or social media were entered in a random drawing of five Amazon gift cards, each worth $5.00, which were sent electronically. Students who were recruited through CSU's SONA System portal were not eligible to be entered in the drawing of Amazon gift cards, but instead received 0.50 course credits for their participation.

Sample

A sample of 1,883 participants, aged 18 and older, were included in the initial dataset. We then conducted an extensive data cleaning process (described in further detail in the Procedures section) which provided a resultant sample of 1,518 participants. As our analysis required two separate datasets for exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), we conducted a random split of the 1,518 participants.

Demographics

The participants in the EFA sample (n = 764) ranged in age from 18-93, with a mean age of 48.20. The majority of the participants in the EFA sample were female (63.50%) and White (89.80%). Most of the participants had a degree in higher education, with either a Bachelor's degree (35.60%) or a Master's degree (27.10%) (see Table 1). Approximately 1/3 of the participants were diagnosed with ASC (31.40%). However, the majority of those diagnosed indicated having a self-reported diagnosis (68.30%). Among those diagnosed with ASC, a majority reported being diagnosed with another psychological condition (93.30%), with an average of 3.55 comorbidities. The comorbidities included anxiety, post-traumatic stress disorder, obsessive compulsive disorder, social phobia, depression, bipolar disorder, schizophrenia, schizotypal personality disorder, antisocial personality disorder, avoidant personality disorder, obsessive compulsive personality disorder, borderline personality disorder, illicit drug use, alcohol related disorder, medically unexplained physical symptoms, hypochondriasis or somatoform disorder, an eating disorder, attention deficit hyperactivity disorder, and "other" disorder(s), which could be defined in a textbox. For those without ASC, a

majority reported being diagnosed with a psychological condition other than ASC (67.00%), with an average of 1.77 psychological conditions (see Table 2).

The participants in the CFA sample (n = 754) ranged in age from 18-89 years old, with a mean age of 48.51. Most of the participants in the CFA sample were female (62.60%) and White (88.50%). The majority had a degree in higher education, with either a Bachelor's degree (35.30%) or a Master's degree (30.40%) (see Table 1). Approximately 1/3 of the participants were diagnosed with ASC (34.70%). However, the majority of those diagnosed indicated having a self-reported diagnosis (62.20%). A majority of participants who indicated being diagnosed with ASC reported having a comorbid psychological condition (91.60%), with an average of 3.38 reported comorbidities. For those without ASC, a majority reported being diagnosed with a psychological condition other than ASC (65.20%), with an average of 1.55 psychological conditions (see Table 2).

Table 1

Demographics of EFA and CFA samples

	EFA (n = 764)		CFA (n = 754)	
	Mean	SD	Mean	SD
Age	M = 48.20	SD = 17.69	M = 48.51	SD = 17.75
	N	%	N	%
Gender				
Male	231	30.20	227	30.10
Female	485	63.50	472	62.60
Non-binary/third gender	48	6.30	51	6.80
Prefer not to say	0	0.00	4	0.50
Ethnicity				
Amer. Indian/Alaskan Native	3	0.40	5	0.70
African American	21	2.70	15	2.00
Asian	14	1.80	12	1.60
Hispanic/Latino	19	2.50	21	2.80
Pacific Islander	1	0.10	1	0.10
White	686	89.80	667	88.50
Other	20	2.60	33	4.40
Education				
Some high school	5	0.70	4	0.50
High school diploma/GED	24	3.10	22	2.90
Some college credit	108	14.10	114	15.10
Associate's degree	61	8.00	46	6.10
Bachelor's degree	272	35.60	266	35.30
Master's degree	207	27.10	229	30.40
Doctoral degree	87	11.40	73	9.70

Table 2

Diagnostic Information on ASC and Other Psychological Conditions

	EFA (n = 764)		CFA (n = 754)	
	N	%	N	%
Diagnosis of ASC?				
Yes	240	31.40	262	34.70
No	524	68.60	492	65.30
Who made the ASC diagnosis?				
Self	164	68.30	163	62.20
Psychiatrist	27	11.30	42	16.00
Primary Care Physician	6	2.50	3	1.10
Psychologist	33	13.80	47	17.90
Social Worker	9	3.80	3	1.10
Nurse Practitioner	1	0.40	4	1.70
Comorbid Diagnosis?				
ASC				
Yes	224	93.30	240	91.60
No	16	6.70	22	8.40
Non-ASC				
Yes	351	67.00	321	65.20
No	173	33.00	171	34.80
	Mean	SD	Mean	SD
Average Comorbidities				
ASC	M = 3.55	SD = 0.14	M = 3.38	SD = 0.13
Non-ASC	M = 1.77	SD = 0.08	M = 1.55	SD = 0.72

Note. Comorbid Diagnosis refers to the following question: Are you currently diagnosed with any of the following mental health conditions?

After verifying through mean testing via *t* tests and *z* tests, we determined that there are only two significant differences in terms of demographics between the EFA and CFA groups. When comparing the comorbidities of those without ASC in the EFA and CFA, the EFA group ($M = 1.77$, $SD = 1.75$) was statistically different from the CFA group ($M = 1.55$, $SD = 1.59$), $t(1014) = 2.10$, $p = .04$. Specifically, individuals without ASC in the EFA group had significantly more comorbidities than those in the CFA group without ASC. However, comorbidities must be whole numbers. Therefore, while the finding was significant, the difference between the comorbidities among these two groups should not affect the overall findings of this study. This is because when rounding the comorbidities of individuals without ASC, both the EFA and CFA groups have an average of 2.00 psychological disorders. The second significant difference was found in the gender category of "prefer not to say." When comparing the percentage of people who selected "prefer not to say" in the EFA and CFA, the EFA group ($n = 0$, 0.00%) was significantly smaller than the CFA group ($n = 4$, 0.50%), $z = -2.02$, $p = .04$. However, as this finding demonstrates a difference of zero and four participants who indicated their gender as "prefer not to say," this should not have a large impact on the results of this study.

Materials

This study was conducted using a psychometric research design. All materials were compiled into a survey via Qualtrics Experience Management (XM) Platform (Qualtrics XM, 2020). The Qualtrics survey consisted of an informed consent form, a demographic questionnaire, three questionnaires, and a debrief survey which was completed after the study. Given that participants were recruited through various

methods, those who participated through Cleveland State University's (CSU) Sona System portal received a different version of the informed consent form than the participants who were recruited via ResearchMatch or social media. The three questionnaires included the Autism Spectrum Trait Scale (ASTS), the Ritvo Autism Asperger Diagnostic Scale shortened version (RAADS-14), and the Pictures of Facial Affects (POFA), which were presented to participants in the aforementioned order. The items on the ASTS were presented in a Likert-type scale from one to four, one indicating *false*, two indicating *mostly false*, three indicating *mostly true*, and four indicating *true*. While the RAADS-14 (Eriksson et al., 2013) and the POFA (Ekman & Friesen, 1976) were collected, this study solely utilized the data obtained in the ASTS. The duration of the entire study was estimated to take approximately 15-20 minutes to complete.

Design

Factor Analysis (FA) has been considered the most critical statistical tool in assessing and confirming the structure of measurement instruments (Plichta & Kelvin, 2013). The first stage of FA is exploratory factor analysis (EFA), an exploration of the associations among the items on a questionnaire. These interrelationships reveal clusters of items with common variation which justify grouping the items into factors (Froman, 2001). EFA identifies the relationships between manifest and latent variables by assuming that both types of variables are measured on an interval scale (Fontaine, 2005). Further, the second stage of FA, known as confirmatory factor analysis (CFA), is used to examine whether the proposed factors found in the initial EFA stage were accurate (Froman, 2001). Given that a hypothesized factor structure was created during the initial EFA stage, if the same participants are used for the CFA stage, this will yield an

unreliable good model fit. Thus, we split our datafile in half to conduct an EFA on the first randomly split half of the participants. Next, we conducted our CFA using the second dataset to determine whether our hypothesized factor structure matched reality.

Procedures

Data Cleaning

We initiated the data analytic process by cleaning our dataset. We renamed the variables in the Statistical Package for Social Sciences (SPSS) statistical software and formatted the data to make them easily analyzable. Next, we reverse coded necessary items in the Autism Spectrum Trait Scale (ASTS) and calculated total scores. The ASTS originally consisted of 52 items with 14 reverse coded items (see Appendix A). To ensure the reliability and validity of the data, we examined the dataset to identify participants who exhibited characteristics that potentially threatened the integrity of the data.

The dataset originally included 1,883 participants. Initially, 33 participants were deleted, as 24 of these individuals completed the study without providing their consent, and nine were under the legal age of consent. Further, 176 participants were excluded due to incomplete participation or completing the study in an unreasonably short amount of time. Specifically, anyone who completed less than 90% of the study or completed the study in less than 10 minutes was excluded.

To determine whether outliers were present, we looked at *z* scores and Mahalanobis D. *Z* scores were utilized to identify univariate outliers, and Mahalanobis D was used for the detection of multivariate outliers. We employed a *z* score cutoff of plus or minus two (Schober et al., 2021). After finding *z* scores, 72 participants who had either unusually high or low scores based on our cutoff criteria were excluded. Further,

Mahalanobis D was used to determine multivariate outliers, and 18 participants were removed (Penny, 1996). Finally, we randomly split the file, resulting in two new datasets which were used for conducting exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The dataset used for EFA consisted of 764 participants and the dataset used to conduct a CFA initially comprised 820 participants. However, we deleted missing cases listwise to effectively conduct a CFA using Analysis of Moment Structures (AMOS) (Arbuckle, 2019). Therefore, we ended up with 754 participants in the CFA dataset. After excluding 365 participants based on the aforementioned criteria, our analysis included a total of 1,518 participants.

Exploratory Factor Analysis (EFA)

Extraction Method. Prior to conducting EFA procedures, it is necessary to determine what extraction method will be used. There are two main extraction methods used in factor analysis (FA): principal factor analysis (PFA)[1] and principal component analysis (PCA). A systematic study demonstrated that PCA and PFA yielded widely different results when these extraction methods were used on the same datasets (Hubbard & Allard, 1987). Given the distinct underlying assumptions of PCA and PFA, careful consideration should be given when selecting the appropriate factor extraction method prior to data analysis. PFA assumes that measurement error exists in a dataset and focuses on identifying items with shared systematic variation (Froman, 2001). Some studies assert that PFA is the 'preferred' or 'better' method of extraction (Ballester et al., 2005; Costello & Osborne, 2005). However, PFA restricts a scale from considering

[1] It is important to note that PFA is also referred to as common factor analysis (CFA), and principal axis analysis (PAA). However, for the purposes of this study, we will only be referring to this extraction method as PFA.

unique single items. On the other hand, PCA operates on the assumption that there is no error in measurement, and therefore considers all variations among items to be interpretable. We utilized the latter approach because we did not have an a priori hypothesis, we were uncertain about the optimal number of factors, and we did not know how many items we would have per factor. Therefore, PCA's underlying assumption was better suited for our analytic process.

Testing Assumptions. The Statistical Package for Social Sciences (SPSS) statistical software was used to conduct our exploratory factor analysis (EFA) procedures (IBM Corp., 2021). To prepare for EFA, all of the assumptions were tested to ensure that the psychometric properties of the ASTS would be effectively determined. As indicated by the inclusion of only metric variables in the dataset, the variable assumption was satisfied. Further, to ensure adequate sampling, there should be at least 10 participants for each item in a scale. Given that the ASTS initially had 52 items, the inclusion of 764 participants was above the required sample size of 520 participants. Upon testing the preliminary assumptions above, we tested the other assumptions of EFA including independence of errors, linearity, absence of outliers, lack of extreme multicollinearity, underlying structure, and homogeneous intercorrelations by subgroups.

The independence of errors assumption is a theoretical assumption. Therefore, as this study employed a random sampling recruitment method with no prerequisites necessary for participation, the independence of errors assumption was met. A linear relationship is assumed based on a comparison of the ASTS items conducted via individual scatterplot matrices. In regard to absence of outliers, both univariate and multivariate outliers were evaluated. A *z* score cutoff of plus or minus two was employed,

which identified 72 univariate outliers (Schober et al., 2021). Multivariate outliers were identified using Mahalanobis D, resulting in 18 participants being removed from the analysis (Wicklin, 2012).

The existence of an underlying factor structure is a theoretical assumption. Given that each item was designed to capture an aspect of ASC, we assume that there is an underlying factor structure present. To determine whether individual items had too much multicollinearity, the partial correlation values of an anti-image matrix were evaluated using an absolute cutoff value of .70. While no values exceeded the cutoff, there were two items, items 15R and 19R, which came close to the cutoff (discussed in further detail in the Item Retention section). Finally, we theorized that there were homogeneous intercorrelations by subgroups, as it was assumed that items would load on each factor consistently across different subgroups.

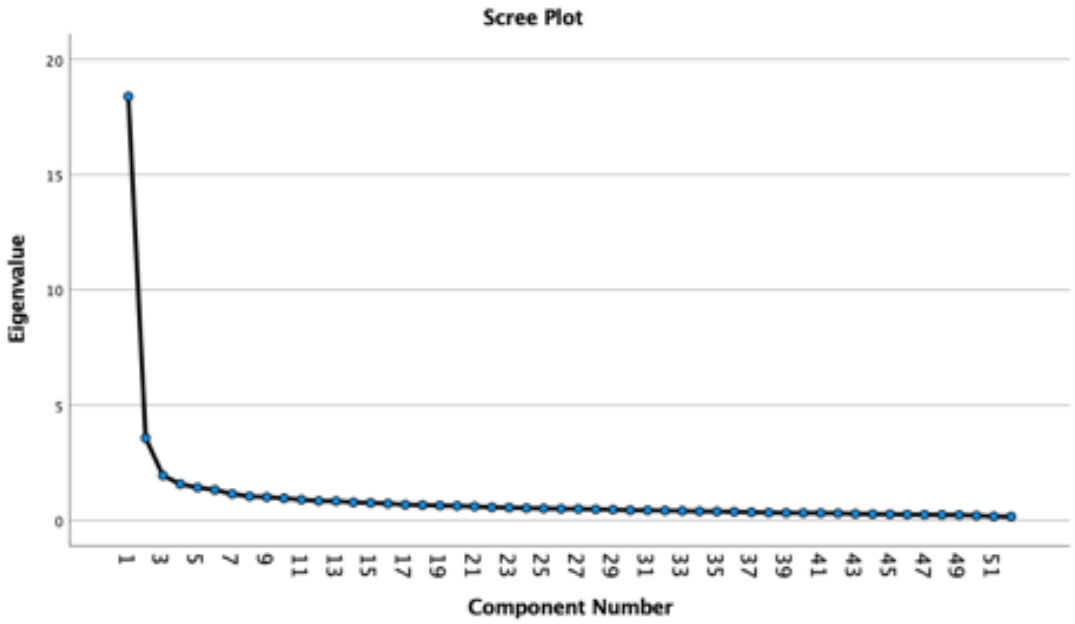
Assessing Multicollinearity. Pairwise deletion was employed as this method considers cases that contain some type of missing data. Kaiser-Meyer-Olkin measure of sampling adequacy (KMO-MSA) and Bartlett's test of sphericity were used to determine sufficient sampling adequacy and multicollinearity to proceed with EFA. KMO-MSA values of above .90 are described as 'marvelous' and values that are equal to or below .50 are considered unacceptable (Kaiser, 1974). We obtained a KMO-MSA value of .96 and a significant Bartlett's test of sphericity, $\chi^2(1326) = 21759.76$, $p = .000$, which indicated that the EFA was appropriate to merit factor analysis. Finally, individual item-level MSA values were evaluated using a cutoff of above .50, and all values met the threshold to indicate sufficient multicollinearity.

Factor Retention Procedures. Four statistical tests were conducted to determine how many factors would be retained for the EFA. Initially, the latent root criterion[2] method was used to examine the eigenvalues, considering factors with an eigenvalue greater than 1.00. The data suggested that nine factors be retained, with the ninth factor having an eigenvalue of 1.02. Similarly, the percent of variance in terms of total variance also suggested retaining nine factors, as nine factors explained 60.53% of the variance. This was determined based on a cutoff value of 60%, where factors accounting for greater than 60% of the variance were retained. Further, the percent of variance in terms of individual factor contributions was evaluated, where factors accounting for greater than 5% of the variance were retained. Interestingly, this method suggested the retention of only two factors, with the second factor accounting for 6.88% of the variance. The final method, the scree plot, also yielded the retention of two factors, determined by the inflection point (see Figure 1).

[2] It is important to note that latent root criterion is also referred to as kaiser criterion, unity criterion, or kaiser-guttman criterion. For the purposes of this study, we will only be referring to this concept as latent root criterion.

Figure 1

Scree Plot for Determining Factor Retention



Note. To determine factor retention using a scree plot, count the number of line segments prior to the inflection point.

Factor Retention Discrepancy. If there are discrepancies among factor retention findings, researchers typically rely on their theoretical understanding (Knekta et al., 2019). However, all methods should be considered. Therefore, due to the discrepancy in factor retention results, we duplicated the confirmatory factor analysis (CFA) dataset. The goal was to test the model fit of both a two-factor model and a nine-factor model. We theorized that aligning the ASTS with the two dimensions of ASC outlined in the current diagnostic manual, the DSM-V-TR, would result in a good model fit. Thus, we conducted the two-factor model first. Upon employing the Analysis of Moment Structures (AMOS) statistical software to test the two-factor structure, it was determined that the model did not exhibit a good model fit, as indicated by the goodness of fit statistics. Therefore, the remainder of this study solely reports on the information obtained during the nine-factor

EFA and CFA procedures. It is important to note that the EFA and CFA procedures remained consistent throughout the entire analytic process of the two-factor and nine-factor analyses. Additionally, there were no changes or modifications made to the datasets at any point[3].

Rotation Method. A promax rotation, a type of oblique method, was used to allow factors to correlate with each other to determine the best factor solution. Due to the nature of the Autism Spectrum Trait Scale (ASTS), the factors were assumed to be correlated with each other based on the scale being designed to measure the overall construct of ASC. Upon employing promax rotation, it was determined that the model converged within 10 iterations, meeting the acceptable criteria that a model must converge in less than 25 iterations.

Item Retention. To determine which items to retain, we identified "bad" items that either did not load on any factor or were cross-loading on more than one factor (Field, 2017). Each item was deleted iteratively. After each iterative attempt, all of the assumptions were reevaluated. The item retention process began with the deletion of cross-loading items, using both statistical values and theoretical considerations. Items with values of above .30 on multiple factors were considered cross-loading items. After all cross-loading items were removed, the items that did not load on any factor were eliminated, indicated by having values lower than .30 on all factors.

[3] All versions of the analyses were saved to maintain data integrity and transparency for potential verification by publishers or other interested parties.

There were originally 11 bad items, two of which were non-loading items and nine were cross-loading items. During the 15th iterative attempt, the partial correlation value for items 15R and 19R increased to .69. Compared to other partial correlation values, the value associated with items 15R and 19R was much higher and was also very close to the recommended cutoff of .70. The two items were also believed to have the same theoretical meaning. Therefore, we employed a 16th iterative attempt by deleting item 15R due to high multicollinearity. In summary, 18 of the initial 52 items were deleted, resulting in a 34 item scale. As items were deleted, the number of factors retained decreased based on the eigenvalues (see Table 3). For instance, in the second iterative attempt, the eigenvalue for the ninth factor dropped below 1.00, indicating that the ninth factor should be deleted.

Factor Loadings. As shown in the table above, the nine factor solution was reduced into a six factor solution. Factor 1 had seven items, Factor 2 had seven items, Factor 3 had six items, Factor 4 had four items, Factor 5 had six items, and Factor 6 had four items. All of the remaining items loaded above .40 on a single factor. The factors were named based on a comprehensive understanding of all items that grouped in each factor (see Table 4).

Table 3

Exploratory Factor Analysis (EFA) Iteratively Deleted Items

Iterative Attempt	Deleted Item	Number of Factors	Remaining Bad Items
1	Q39	9	11
2	Q5R	8	13
3	Q38R	8	13
4	Q43R	7	16
5	Q20R	7	15
6	Q16R	7	8
7	Q27	7	7
8	Q45	7	7
9	Q3R	7	6
10	Q1	7	6
11	Q35	7	5
12	Q9	7	4
13	Q22	7	3
14	Q17R	7	1
15	Q40	7	0*
16	Q15R	6	3
17	Q19R	6	2
18	Q26	6	0

Note. Item 15R was removed during the 16th iterative attempt due to multicollinearity.

Table 4

The Autism Spectrum Trait Scale Items Grouped Per Factor

Item	Question	Factor Loadings					
		F1	F2	F3	F4	F5	F6
Factor 1: Social-Emotional Integration							
Q4	I often take things people say literally, and I have been told I am misunderstanding the point of what they are saying.	.61					
Q8R	I am great at picking up social hints and cues.	.85					
Q13	It is relatively DIFFICULT for me to "read" how people feel.	.80					
Q18	It is difficult for me to KNOW when someone says one thing but actually means something else.	.76					
Q23R	It is easy for me to figure out how other people feel.	**.91**					
Q25	It is difficult for me to figure out the social games people play.	.64					
Q28	I have been told I am very literal in my thinking.	.62					
Factor 2: Stereotyped or Repetitive Motor Movements, Objects, or Speech							
Q6	People sometimes tell me that I talk too loudly or softly, but I don't notice myself doing it.		.47				
Q10	People have commented that I have difficulty maintaining eye contact.		.64				
Q11	When I was a teenager, some people commented that I talk in a strange way.		.81				
Q12	I have been told that my facial expressions don't match how I really feel.		**.82**				
Q29	I have trouble understanding why people use expressions such as "break a leg", "bite the bullet", "stabbed in the back".		.79				
Q34	I find myself staring at objects such as fans and lights.		.66				
Q42	When I was young, I often engaged in repetitive behavior such as rocking OR hand-flapping.		.68				
Factor 3: Restricted and Sensory Behaviors							
Q14	It is difficult for me to be in a conversation I am not interested in.			.52			
Q24	Sometimes a thought or a subject gets stuck in my mind, and I really want to talk about it even if no one is interested.			.44			
Q36	From a very young age, I have been sensitive to certain sounds.			.86			
Q37	I feel uncomfortable wearing certain clothing.			.74			
Q41	I often feel uneasy when I am in a place where there are many smells, noises, or bright lights.			.89			
Q44	It is difficult for me to tolerate things I dislike (like smells, textures, sounds or colors).			**.94**			
Factor 4: Highly Fixated Interests							
Q47	I like collecting items on certain topics, but many people tend to show little interest in my collection(s).				.82		
Q50	I like to collect information about certain topics like cars, birds, trains, computers, TV shows, etc.				.81		
Q51	I have special hobbies that only a few people have.				.74		
Q52	I enjoy collecting special or "rare" items.				**.96**		
Factor 5: Nonverbal Behavior and Interpersonal Relationships							
Q2	When I was young, I sometimes offended people by what I said, but I didn't mean to.					.45	
Q7	When I was young, others considered me odd or different.					.82	
Q30	When I was young, I had few close friends.					**.99**	
Q33	Others consider me odd or different.					.64	
Q46	When I was young, I sometimes did things that were considered 'socially inappropriate', but I did not realize it.					.49	
Q48	I have a hard time connecting with members of my family.					.54	
Factor 6: Developing, Maintaining, and Understanding Relationships							
Q21R	It is easy for me to get dates with romantic partners.						**.85**
Q31	I have a hard time forming romantic relationships or getting past the first date.						.73
Q32R	It is easy for me to maintain long-term romantic relationships.						.68
Q49R	It is easy for me to ask potential partners on dates.						.71

Note. The factor loading that is bolded indicates the highest factor loading for each factor.

Confirmatory Factor Analysis (CFA)

Preparation for Conducting CFA. The Analysis of Moment Structures (AMOS) statistical software was used to conduct the CFA procedures. Before transferring the CFA dataset from the Statistical Package for Social Sciences (SPSS) statistical software into AMOS, cases were deleted listwise to ensure that participants had a complete set of answers for the analysis in AMOS[4]. As a result, 66 participants were deleted, and only 754 of the original 820 participants from the random datafile split were analyzed. The six latent constructs (Factors 1-6) were inputted into AMOS to initiate the analysis. Next, preliminary information was obtained to ensure that AMOS yielded accurate results. The preliminary information obtained included calculating the number of pieces of information input into AMOS, estimating the number of parameters, and determining the degrees of freedom (dfs).

A total of 595 pieces of information were input into AMOS, and 83 parameters were estimated. The estimated number of parameters was determined using the paths, covariances, variances associated with the latent constructs (aka latent exogenous variable variances), and residual variances. To determine the number of paths, the manifest variables were subtracted by the number of factors, indicating 28 paths. Six latent exogenous variables were identified, as this is equal to the number of the latent constructs. As we allowed every latent construct to covary with one another, there were a total of 15 covariances. To determine the residual variance, the number of errors associated with the manifest variables were used, resulting in 34 residual variances.

[4] AMOS deviated from its typical analytic procedures when pairwise deletion was employed.

Finally, we calculated 512 degrees of freedom by subtracting pieces of information by the number of parameters.

Testing Assumptions. To prepare for CFA, all of the assumptions were tested to ensure that the psychometric properties of the ASTS would be effectively determined. To ensure adequate sampling, two rules serve indicators that suggest a sufficient sample size. One rule is that there should be at least 10 participants per variable in a dataset. As there are 34 items in the ASTS, the inclusion of 754 participants was above the required sample size of 340 participants. The second rule states that there should be at least 5 times the number of participants as parameters estimated. As 83 parameters were estimated, the inclusion of 754 participants was above the required sample size of 415 participants. Therefore, we had a sufficient sample size for both rules.

There are also model identification assumptions for CFA that must be justified at both local and overall identification levels. Local identification is considered adequate when there are a minimum of four items per latent construct. As there at least are four items in each factor, local identification was achieved. Further, overall identification is sufficient if the model has positive degrees of freedom (dfs). As 512 degrees of freedom is positive, the model was over-identified in terms of overall identification. After testing all relevant assumptions, modification indices were requested with a cutoff of 4.00. To scale the latent constructs, the first item on each factor's path loading (standardized regression weight) was set to 1.00.

CHAPTER III

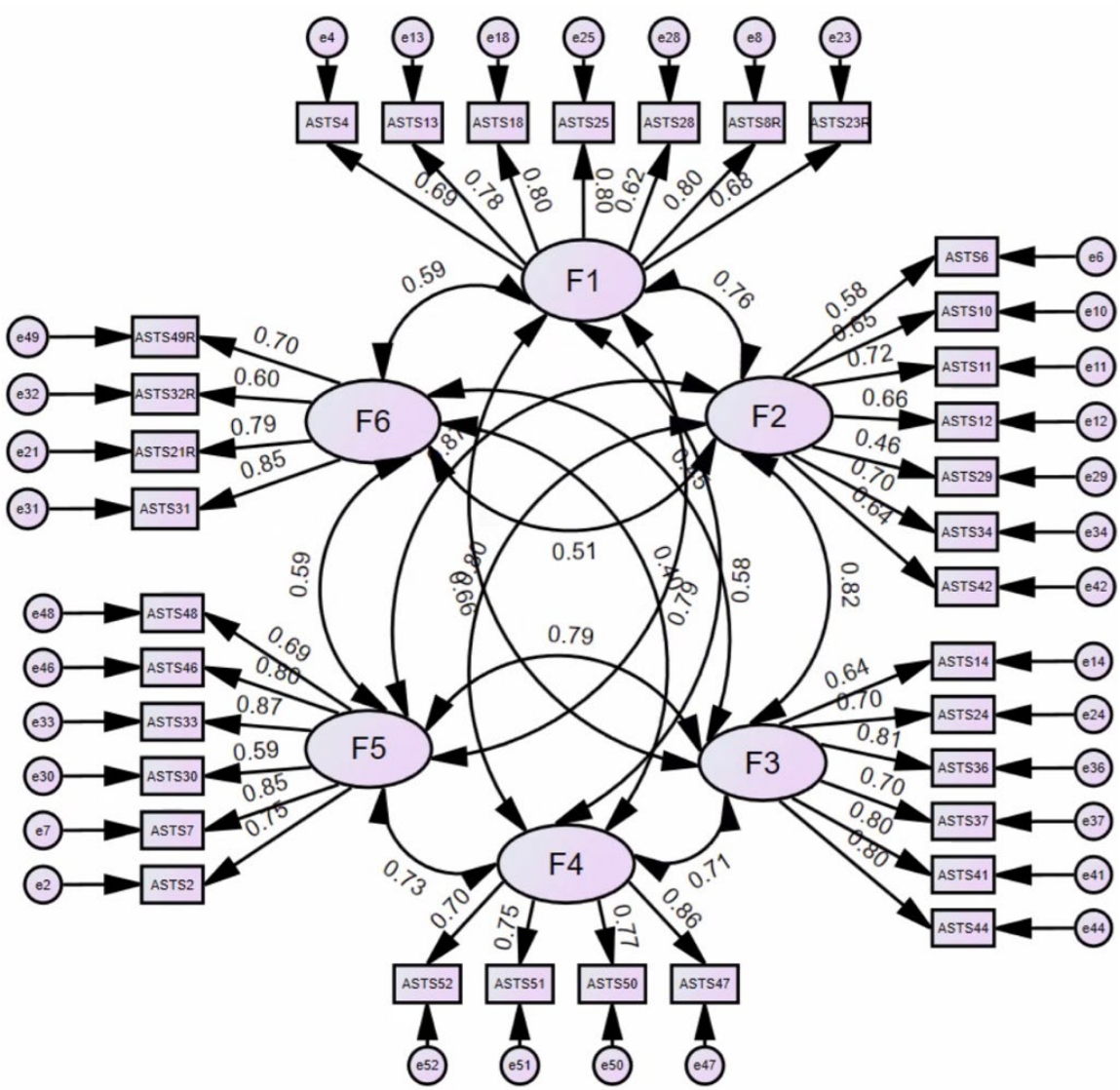
RESULTS

Model Fit Indices

Confirmatory factor analysis (CFA) was conducted using maximum likelihood estimation and standardized regression coefficients. The model converged and the chi-square (χ^2) value was significant, indicating a bad model fit (χ^2) (512) = 1651.96, p = .000 (see Figure 2). However, as chi-square is heavily influenced by sample size, a significant chi-square value can be overlooked (Barnard-Brak et al., 2020). The four model fit statistics evaluated were the Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), Goodness of Fit (GFI), and root-mean-square error of approximation (RMSEA). Values greater than or equal to .90 for TLI, CFI, and GFI are indicative of a good model fit (Hu & Bentler, 1998). The TLI and CFI indicated a good model fit, with values of .92 and .92, respectively. The GFI had a value of .88, which is slightly below the cutoff. Finally, RMSEA yielded a value of .05, with values less than or equal to .05 indicating a good model fit. As three out of four different fit statistics indicated a good model fit, and one was only slightly below the cutoff, we concluded that the six-factor model was a good fit.

Figure 2

Confirmatory factor analysis for the Autism Spectrum Trait Scale



Note. All of the values presented in the CFA were in standardized form.

Further, to determine if our hypothesized factor structure was correct, we examined whether the items loaded onto their intended constructs. A significant path loading from the latent construct to an item indicates that the item fits within its designated construct. All items had a *p* value that was below .05, indicating that the

hypothesized factor structure was correct. Specifically, each of the item's *p* value was below .001.

Construct Validity. Construct validity was assessed through the measurements of both convergent validity and discriminant validity (Hahs-Vaughn, 2017). Convergent validity determines how strongly the items on each factor group together (Cheung et al., 2023). Discriminant validity determines whether two factors are measuring different constructs or the same construct (Rönkkö & Cho, 2022).

The average variance extracted (AVE) values were used to determine convergent validity among all factors. The AVE values were obtained by calculating the average of the squared standardized regression weights for each factor. The cutoff criterion for AVE values indicating good convergent validity is a value of greater than or equal to .50 (Cheung et al., 2023). All of the factors, except Factor 2, had good convergent validity, with all the AVE values being greater than .50. Factor 2 had a value of .40 which is below the cutoff for good convergent validity. The low squared standardized regression weight of Item Q29 suggests that this item may not correlate with the other items in this factor, which may have contributed to poor convergent validity (see Table 5).

To determine discriminant validity, the square roots of the AVE values were compared to the correlation value associated with each set of two factors. Discriminant validity is considered good when the correlation value in the associated row or column of the correlation matrix is less than the square roots of the AVE values, signifying that two factors measure different constructs (see Table 5). Conversely, poor discriminant validity is an indicator that two factors might be measuring similar constructs. For example, Factors 1 and 3 demonstrated good discriminant validity with a correlation value of .66,

which was lower than the square roots of the AVE values, which were .74 and .74, respectively. Whereas Factors 1 and 2 had poor discriminant validity, given that their correlation of .76 was higher than the square roots of their AVE values, which were .74 and .63, respectively. However, because a promax rotation method was employed during EFA, we expected that some of the factors might be correlated.

Table 5

Convergent & Discriminant Validity

	AVE	F1	F2	F3	F4	F5	F6
F1	.55	**.74**					
F2	.40	.76	**.63**				
F3	.55	.66	.82	**.74**			
F4	.60	.58	.80	.71	**.77**		
F5	.59	.79	.87	.79	.73	**.77**	
F6	.55	.59	.51	.45	.40	.59	**.74**

Note. Convergent validity is considered bad if the AVE value is less than .50.

Hierarchical Testing: Justifying a Second-Order Model

Upon analyzing the items per factor, it became evident that each factor may be associated with a higher-order construct of either Criteria A or Criteria B for ASC in the DSM-V-TR. Subsequently, two new latent variables, namely Criteria A or Criteria B, were added as second-order latent constructs. We theorized that Factors 1, 2, 5 and 6 would load on the higher-order latent construct of Criteria A's descriptors for DSM-V-TR (APA, 2022). Whereas Factors 3 and 4 were observed to load onto the higher-order latent construct representing Criteria B (see Table 6).

Table 6

The Theory for an Attempt at a Second-Order Model

Factor 1	Criteria A	Factor 2	Criteria A	Factor 3	Criteria B
Q4	A1	Q6	A2	Q14	B3
Q8R	A1	Q10	A2	Q24	B3
Q13	A1	Q11	A2	Q36	B4
Q18	A1	Q12	A2	Q37	B4
Q23R	A1	Q29	A2	Q41	B4
Q25	A1	Q34	B4	Q44	B4
Q28	A1	Q42	B1		
Factor 4	Criteria B	Factor 5	Criteria A	Factor 6	Criteria A
Q47	B3	Q2	A1	Q21R	A3
Q50	B3	Q7	A3	Q31	A3
Q51	B3	Q30	A3	Q32R	A3
Q52	B3	Q33	A3	Q49R	A3
		Q46	A1		
		Q48	A3		

Note. DSM-V-TR Criteria A focuses on social communication and interaction deficits. The DSM-V-TR Criteria B focuses on restricted and repetitive behaviors, interests, or activities (APA, 2022).

To begin conducting the second-order model, the covariances were deleted from the original six factors inputted in Analysis of Moment Structures (AMOS) statistical software. Further, we added error terms to each of the new factors and made the new latent constructs covary with each other. Finally, we fixed the path loadings of the first item of each factor to be 1.00 (see Figure 3). The first two fit statistics, TLI and CFI, indicated a good model fit, with values of .91 and .92, respectively. However, the GFI and RMSEA yielded poor and moderate model fit, with values of .87 and .06, respectively. Upon evaluating the overall fit statistics, we determined that the second-

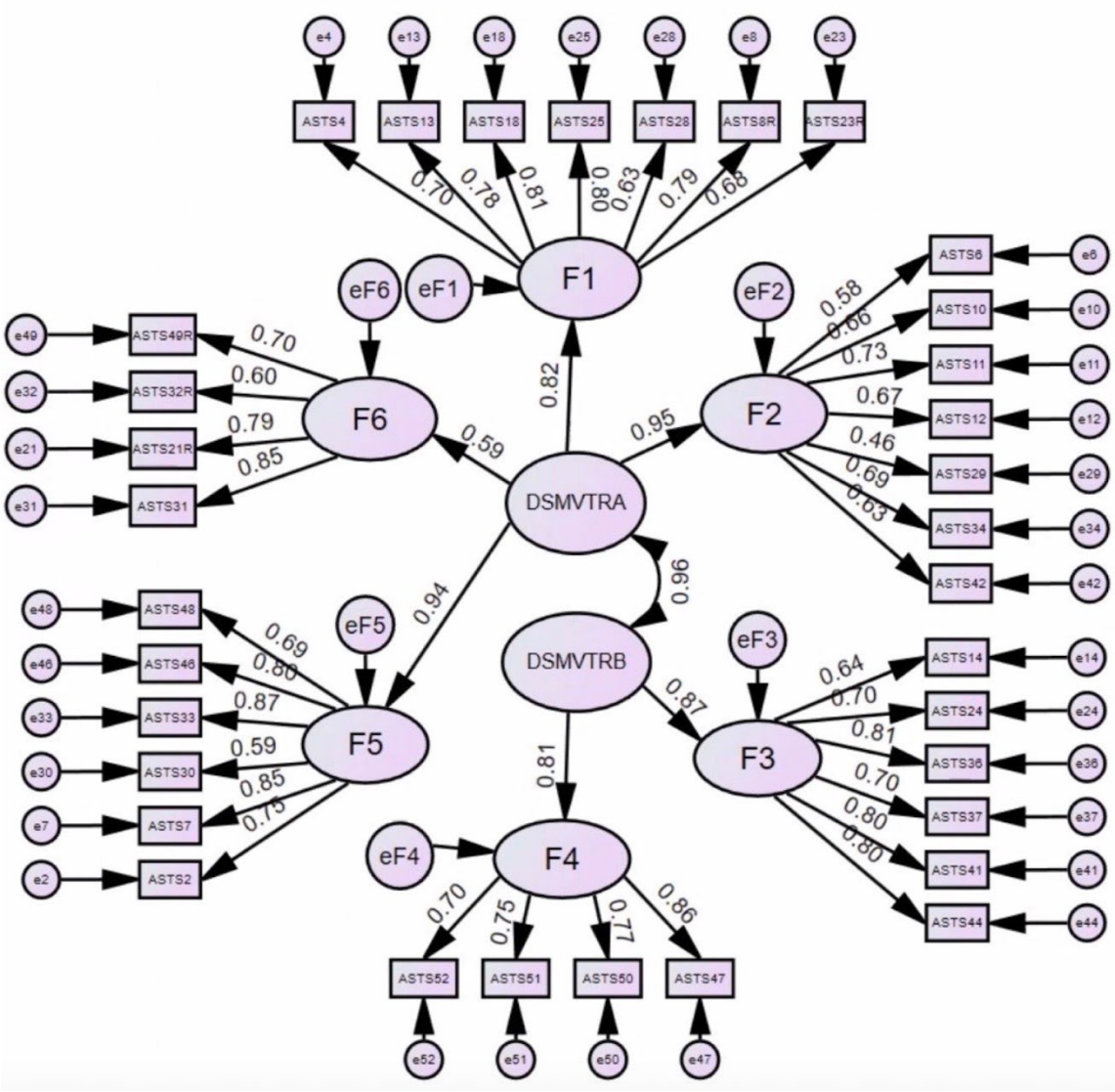
order model had a moderate fit. Further, the path loadings from the second-order latent constructs to the original six factors were all significant.

Construct Validity of the Second-Order Model

The second-order model's construct validity was established by calculating the average variance extracted (AVE) values for each factor. As AVE values of greater than or equal to .50 indicate good convergent validity, Criteria A exhibited good convergent validity, with an AVE value of .70. Likewise, Criteria B had good convergent validity, with an AVE value of .71. Moreover, we determined the discriminant validity between the two second-order latent constructs. Discriminant validity was considered good if the correlation value was less than the square roots of the AVE values. The second-order latent construct's correlation value was .96, whereas the square roots of the AVE values were .84 and .84. Thus, the poor discriminant validity between the second-order latent constructs suggests that they are not different enough to justify being classified as a hierarchical model.

Figure 3

Confirmatory Factor Analysis for the Second-Order Model



Note. All of the values presented in the CFA were in standardized form.

Determining Measurement Invariance

Despite the six-factor model revealing a good model fit during the confirmatory factor analysis (CFA) procedures, the next step is to ascertain measurement invariance. Measurement invariance refers to the idea that a construct has a consistent meaning among different groups or across different points in time (Putnick & Bornstein, 2016).

Without establishing measurement invariance, the ASTS does not operate in the same way among different groups when measuring the construct of ASC. Therefore, the comparison between different groups could be invalid. To test for invariance, we ran two baseline models in AMOS using multiple groups confirmatory factor analysis (MGCFA). The first baseline model included participants with ASC and the other utilized data from all participants without ASC, which included both neurotypicals and individuals with any other psychological conditions besides ASC (see Table 7).

Conducting a Multiple Group Confirmatory Factor Analysis

Multiple groups confirmatory factor analysis (MGCFA) was used to run the following models in Analysis of Moment Structures (AMOS): Model 1 (unconstrained), Model 2 (measurement weights), Model 3 (structural covariances), Model 4 (measurement residuals). Model 1 was the unconstrained baseline model, which included individuals with and without ASC. The second model, Model 2, constrained all of the paths to set values and was used to test configural (weak) invariance. Model 3 added additional constraints to the covariances and was used to test metric (moderate) invariance. Finally, Model 4 constrained error terms, covariances, and paths, to test scalar (strong) invariance.

We tested model fit using chi-square (χ^2), comparative fit index (CFI) and root-mean-square error of approximation (RMSEA), with values of CFI $\geq$ 0.90 and RMSEA $\leq$ 0.05 as an indication of good model fit (Hu & Bentler, 1998). Chi-square was tested with the understanding that it is heavily influenced by sample size and is becoming less popular in the literature. Therefore, we primarily relied on CFI and RMSEA to test for invariance . The change (Δ) in RMSEA and CFI was calculated and compared these to

the cutoff values of Δ CFI ≥ -.01 and Δ RMSEA ≥ .015, which would indicate that the model fit got significantly worse (Putnick & Bornstein, 2016).

During our initial comparison of Model 2 to Model 1, we observed a Δ CFI of -.007 and Δ RMSEA of .001, indicating that configural invariance was established (see Table 9). Similarly, Model 3 to Model 2 established metric invariance, with a Δ CFI of -.01 and Δ RMSEA of .001. Finally, when comparing Model 4 to Model 3, we found Δ CFI of -.057 and Δ RMSEA of .007. The Δ CFI of -.057 was above the cutoff value of Δ CFI ≥ -.01. Whereas the Δ RMSEA was still below the cutoff value of Δ RMSEA ≥ .015. However, to demonstrate invariance, both the Δ CFI and the Δ RMSEA must simultaneously agree. Thus, given that the Δ CFI was above the cutoff value of Δ CFI ≥ -.01, this finding indicates that we were unable to effectively demonstrate scalar invariance (see Table 7).

Table 7

Invariance Fit Statistics for the ASC vs. Non-ASC Groups

Model	Fit Indices					Comparison	Δ RMSEA	Δ CFI
	χ2	dfs	p	RMSEA	CFI			
ASC	983.935	512	.000	.059	.840			
Non-ASC	1217.947	512	.000	.053	.893			
Model 1	2202.275	1024	.000	.039	.876			
Model 2	2300.923	1052	.000	.040	.869	2 vs. 1	.001	-.007
Model 3	2414.812	1073	.000	.041	.859	3 vs. 2	.001	-.01
Model 4	2991.155	1107	.000	.048	.802	4 vs. 3	.007	-.057

Note. The criteria cutoffs are as follows: Δ CFI ≥ -.01 and Δ RMSEA ≥ .015 indicates bad invariance. Model 1 (unconstrained), Model 2 (measurement weights), Model 3 (structural covariances), Model 4 (measurement residuals).

Determining the Detection of ASC Using the ASTS

After establishing metric measurement invariance to confirm an adequate good model fit, we determined whether or not the ASTS could effectively detect ASC using the Statistical Package for Social Sciences (SPSS) statistical software. As metric invariance confirms that responses were consistent across groups, the use of mean testing is a dependable method for assessing whether the ASTS can effectively detect ASC. The overall mean and standard deviation (SD) were calculated for the total scores on the ASTS as well as for each individual factor (see Table 8).

Table 8

Average Scores of All Participants

	Range[5]	# of Items	Mean	SD
Total	34-136	34	*M* = 79.83	*SD* = 22.80
F1	7-28	7	*M* = 16.80	*SD* = 5.24
F2	7-28	7	*M* = 12.88	*SD* = 4.91
F3	6-24	6	*M* = 16.07	*SD* = 5.22
F4	4-16	4	*M* = 8.85	*SD* = 3.68
F5	6-24	6	*M* = 15.32	*SD* = 5.29
F6	4-16	4	*M* = 10.64	*SD* = 3.40

Further, *t* tests were conducted to compare participants with and without ASC, to determine whether those with ASC scored significantly higher on the ASTS than those without ASC (see Table 9). When comparing the total scores of all participants in the CFA dataset on the ASTS scale, those with ASC (*M* = 101.61, *SD* = 14.51) scored significantly higher than those without ASC (*M* = 68.23, *SD* = 17.24), *t*(615.79) = 28.13, *p* = <.001. Likewise, when comparing the Factor 1 scores, those with ASC (*M* = 20.36,

[5] In this table and all the subsequent tables, the "Range" refers to the entire possible range of scores participants could have obtained.

SD = 4.14) scored significantly higher than those without ASC (*M* = 13.80, *SD* =4.24), *t*(752) = , *p* = <.001. For Factor 2, those with ASC (*M* = 17.17, *SD* = 4.39) scored significantly higher than those without ASC (*M* = 10.60, *SD* = 3.42), *t*(433.34) = 21.07, *p* = <.001. Additionally, the scores from Factor 3 indicated that those with ASC (*M* = 20.29, *SD* = 3.60) scored significantly higher than those without ASC (*M* = 13.82, *SD* = 4.52), *t*(642.38) = 21.46, *p* = <.001.

When comparing the scores of Factor 4, those with ASC (*M* = 11.59, *SD* = 3.23) scored significantly higher than those without ASC (*M* = 7.39, *SD* = 3.01), *t*(752) = 17.79 , *p* = <.001. Likewise, when comparing the Factor 5 scores, those with ASC (*M* = 19.85, *SD* = 3.22) scored significantly higher than those without ASC (*M* = 12.90, *SD* = 4.54), *t*(694.02) = 24.34, *p* = <.001. Finally, for Factor 6, those with ASC (*M* = 12.36, *SD* = 2.97) scored significantly higher than those without ASC (*M* = 9.72, *SD* = 3.26), *t*(577.59) = 11.21, *p* = <.001. In summary, individuals with ASC scored significantly higher than those without ASC in terms of total scores on the ASTS as well as the scores on each individual factor.

Table 9

Average Scores of ASC vs. Non-ASC Participants

		ASC		Non-ASC				
	Range	Mean	SD	Mean	SD	T-value	Dfs	P-value
Total	34-136	101.61	14.51	68.23	17.24	28.13	615.79	<.001
F1	7-28	20.36	4.14	13.80	4.24	20.40	752	<.001
F2	7-28	17.17	4.39	10.60	3.42	21.07	433.34	<.001
F3	6-24	20.29	3.60	13.82	4.52	21.46	642.38	<.001
F4	4-16	11.59	3.23	7.39	3.01	17.79	752	<.001
F5	6-24	19.85	3.22	12.90	4.54	24.34	694.02	<.001
F6	4-16	12.36	2.97	9.72	3.26	11.21	577.59	<.001

Note. The "Range" refers to the entire possible range of scores participants could have obtained.

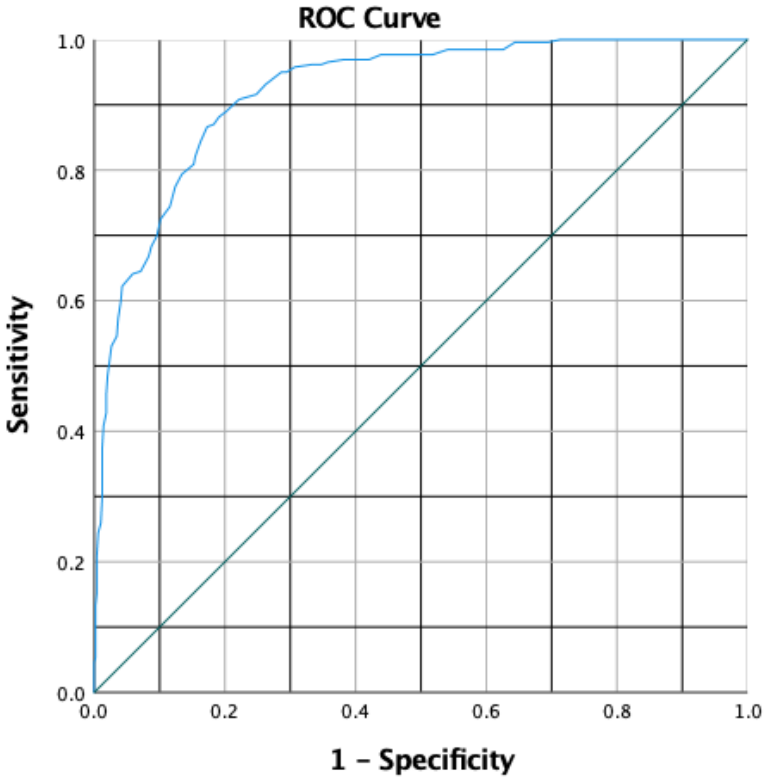
Sensitivity, Specificity, ROC Curves, and AUC Scores

The sensitivity and specificity of the ASTS scale was established by examining receiver operating characteristic (ROC) curves and area under the curve (AUC) scores. Individuals with ASC were compared to those without ASC to determine both the sensitivity and specificity of the ASTS as well as develop diagnostic thresholds. We calculated an ROC curve for the total 34 items as well as for each of the six individual factors. An ROC curve plots the true positive rate (TPR) against the false positive rate (FPR), representing sensitivity and specificity, respectively (Metz, 1978). A TPR indicates the proportion of individuals who were predicted to have ASC being correctly identified as having ASC. Whereas one minus the FPR represents those who were incorrectly predicted to have ASC.

Upon visual analysis, ROC curves that are closer to the top left corner of the graphic representation indicate more accurate assessment of the individuals analyzed. Whereas ROC curves that are closer to the diagonal line indicate that the assessment is less accurate. The AUC scores determine how accurate a scale is at detecting a diagnosis by providing a statistical value. The range for AUC scores is zero to one, with higher values indicating a more accurate scale. Values above .70 are accepted among the literature, however, values closer to one indicate higher levels of accuracy (Mandrekar, 2010). An ROC curve comparing the total scores of participants with ASC (n = 262) and non-ASC (n = 492) yielded an AUC score of .92 (see Figure 4). The ROC curves computed for the individual factors yielded AUC scores ranging from .72 to .88 (see Table 10).

Figure 4

ROC Curve of Total Scores



To determine a hypothetical diagnostic threshold for ASC, we visually analyzed the ROC curve to find the closest point to the top left corner and its corresponding threshold value. The threshold for the total scores was 84.50, which was based on the participants' overall scores on the 34 items. Individuals who scored below the threshold value were not displaying autistic traits, as indicated by their overall score on the ASTS. Whereas those who scored above the threshold value were identified as displaying traits of ASC. Additionally, we calculated thresholds for each of the six factors using the same procedure as was employed while calculating the overall threshold (see Table 10).

Table 10

Sensitivity, Specificity, AUC, and Diagnostic Thresholds

	Range	# of items	AUC	Y axis	X axis	Threshold
Total	34-136	34	.92	.87	.18	84.50
F1	7-28	7	.86	.82	.25	16.50
F2	7-28	7	.88	.84	.24	12.50
F3	6-24	6	.86	.87	.29	16.50
F4	4-16	4	.82	.76	.24	9.50
F5	6-24	6	.88	.79	.19	17.50
F6	4-16	4	.72	.75	.38	10.50

Note. The Y axis represents sensitivity, and the X axis represents 1.00 minus specificity.

CHAPTER IV

DISCUSSION

As an attempt to develop a self-report scale for detecting autism spectrum condition (ASC) in adults, the *Autism Spectrum Trait Scale* (ASTS), this study conducted both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). With a substantial sample size, it was possible to conduct a random split and use half of the participants in the EFA and the other half in the CFA, while maintaining the sample size requirements necessary for the analyses. Due to a discrepancy among factor retention results, both two-factor and nine-factor solutions were examined. The two-factor solution was examined first but did not yield a good model fit when tested in CFA. After iteratively deleting 18 of the original 52 items, the nine-factor solution converged into a six-factor solution. CFA demonstrated that the six-factor solution had a good fit to the data.

To examine the construct validity, both convergent and discriminant validity analyses were conducted. The convergent validity analysis showed that all of the factors had good convergent validity except for Factor 2. Additional analysis showed that certain factors did not exhibit ideal discriminant validity. This finding is not surprising, however, given that this scale was developed to assess a single construct, ASC. Further, it was

theorized that the six-factor solution could be associated with a higher-order construct of either the DSM-V-TR's Criteria A or Criteria B for ASC. However, upon conducting the analysis, poor discriminant validity suggested that the second-order latent constructs were not different enough to justify a hierarchical model. Measurement invariance was conducted using multiple group confirmatory factor analysis (MGCFA), and metric invariance was established.

Further, we sought to determine whether the ASTS could accurately detect the participants who reported having ASC. Mean testing revealed that individuals with ASC scored significantly higher than those without ASC for both their scores on the ASTS total scale and each individual factor. To evaluate sensitivity, specificity, and hypothetical diagnostic thresholds, we used receiver operating characteristic (ROC) curves and an area under the curve (AUC) scores. The analysis showed promising results, with adequate ROC curves and high AUC scores, indicating that the ASTS was able to detect ASC in participants who reported having a diagnosis.

Limitations

This study had several limitations. First and foremost, a majority of participants self-reported having a diagnosis of autism spectrum condition (ASC). As this finding highlights the importance of an accurate and reliable self-report assessment for undiagnosed adults, it is necessary to acknowledge that these self-reported cases are not verifiable. Nevertheless, the method of relying on self-reported diagnoses allows for the collection of large samples, which may not be possible if data are only collected from individuals with a formal diagnosis. That said, future studies of the ASTS would benefit

from identifying formally diagnosed cases of ASC and could use those cases to further validate the diagnostic utility of the measure.

Another noteworthy limitation pertains to the use of ResearchMatch as the primary recruitment method. As ResearchMatch utilizes individuals residing in the United States, the resulting sample lacked representatives from other regions and cultures. Specifically, the majority of respondents were White and female. Consequently, the ASTS psychometric properties and norms may not be generalizable to those of various other groups within the United States including males and minorities.

Future Directions

As mentioned previously, it is pertinent that future research examines the diagnostic abilities of the ASTS by comparing formally diagnosed adults with ASC to those who self-reported their diagnosis because they believe they meet the criteria. Performing such an analysis may yield different results than were obtained in this study, thereby providing additional evidence of the under-diagnosis of ASC in adults. Another direction for future research involves verifying the findings of the ASTS by conducting a test-retest analysis.

While it was not assessed in this study, data was obtained from participants using the items on the Ritvo Autism Asperger Diagnostic Scale shortened version (RAADS-14). Therefore, additional analysis comparing the RAADS-14 to the responses on the ASTS would yield greater insight into the convergent validity of the new scale. Further, given the implications involved in using a single diagnostic threshold to warrant a diagnosis of ASC, it would be advisable to examine whether ASC could fall under different levels of symptomatology, such as low, medium, or high. Likewise, the impact

of age on the endorsement of symptoms could provide valuable insight and expand our understanding of the varying responses to a diagnosis across different stages of life.

Finally, future studies could benefit by embedding the items on the ASTS into another psychological questionnaire. When multiple items address the same construct, as does the ASTS, it may lead to an acquiescent response style, influenced by the respondent's awareness of the construct under evaluation. Thus, assessing how the embedding of ASTS items influences the response pattern of participants could yield valuable insight.

Conclusion

The current study provides evidence that the 34-item Autism Spectrum Trait Scale (ASTS) is a reliable and valid self-report measure for detecting autism spectrum condition (ASC) in adult individuals. Namely, we established that the ASTS has a stable six-factor structure verified through extensive exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) procedures, adequate psychometric properties, effective detection of ASC, metric measurement invariance, and relatively high sensitivity and specificity. These findings provide a robust basis for both future research and the utilization of the ASTS as a component of assessment for ASC in adults.

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APPENDIX A

The Autism Spectrum Trait Scale: The Original 52 Items

Table A1

Items	Questions	Items	Questions
Q1	I like to repeat words or phrases that I've previously heard during conversations.	Q27	It takes a lot of effort for me to make friends.
Q2	When I was young, I sometimes offended people by what I said, but I didn't mean to.	Q28	I have been told I am very literal in my thinking.
Q3R	People have commented that I have great social skills.	Q29	I have trouble understanding why people use expressions such as "break a leg", "bite the bullet", "stabbed in the back".
Q4	I often take things people say literally, and I have been told I am misunderstanding the point of what they are saying.	Q30	When I was young, I had few close friends.
Q5R	I could be a great manager.	Q31	I have a hard time forming romantic relationships or getting past the first date.
Q6	People sometimes tell me that I talk too loudly or softly, but I don't notice myself doing it.	Q32R	It is easy for me to maintain long-term romantic relationships.
Q7	When I was young, others considered me odd or different.	Q33	Others consider me odd or different.
Q8R	I am great at picking up social hints and cues.	Q34	I find myself staring at objects such as fans and lights.
Q9	I have been told I have a "teacher's" (academic) style of speaking like I am lecturing.	Q35	I tend to notice details in patterns of ordinary objects.
Q10	People have commented that I have difficulty maintaining eye contact.	Q36	From a very young age, I have been sensitive to certain sounds.
Q11	When I was a teenager, some people commented that I talk in a strange way.	Q37	I feel uncomfortable wearing certain clothing.
Q12	I have been told that my facial expressions don't match how I really feel.	Q38R	I watch how others dress and try to keep up with fashion.
Q13	It is relatively DIFFICULT for me to "read" how people feel.	Q39	When I eat I don’t like it when different foods are touching.
Q14	It is difficult for me to be in a conversation I am not interested in.	Q40	I try to avoid certain foods because of their texture.
Q15R	I can easily chat and make small talk with strangers.	Q41	I often feel uneasy when I am in a place where there are many smells, noises, or bright lights.
Q16R	I am a great listener.	Q42	When I was young, I often engaged in repetitive behavior such as rocking OR hand-flapping.
Q17R	When talking to someone, I have no trouble telling when it is my turn to talk or to listen.	Q43R	I don't easily feel physical pain (I HAVE a high pain threshold).
Q18	It is difficult for me to KNOW when someone says one thing but actually means something else.	Q44	It is difficult for me to tolerate things I dislike (like smells, textures, sounds or colors).
Q19R	It is easy for me to engage in small talk.	Q45	It can be difficult for me to work in a group for projects. I often prefer to work alone.
Q20R	People have told me I would be a great therapist.	Q46	When I was young, I sometimes did things that were considered 'socially inappropriate', but I did not realize it.
Q21R	It is easy for me to get dates with romantic partners.	Q47	I like collecting items on certain topics, but many people tend to show little interest in my collection(s).
Q22	It is hard for me to tell when someone is flirting with me.	Q48	I have a hard time connecting with members of my family.
Q23R	It is easy for me to figure out how other people feel.	Q49R	It is easy for me to ask potential partners on dates.
Q24	Sometimes a thought or a subject gets stuck in my mind, and I really want to talk about it even if no one is interested.	Q50	I like to collect information about certain topics like cars, birds, trains, computers, TV shows, etc.
Q25	It is difficult for me to figure out the social games people play.	Q51	I have special hobbies that only a few people have.
Q26	When I was a teenager, I had the tendency to flip conversations back on to myself, or to topics I was interested in.	Q52	I enjoy collecting special or "rare" items. (.60)

Note. The items that have an “R” indicate items that were reverse coded.

APPENDIX B

Flyer for Recruitment

- Are you 18 years or older?
- Are you diagnosed with autism spectrum disorder (ASD)?

This research study is looking to assess the reliability of a new measure for detecting autism spectrum disorder (ASD). We are inviting volunteers with and without a history of ASD to participant in this study. This study is open to individuals ages 18 and above. This questionnaire consists of 81 questions and a facial affect recognition task. Participation in this study takes approximately 25 minutes to complete. You may scan the QR code below to participate.

If you have any questions please contact the primary investigator: Dr. Amir Poreh (a.poreh@csuohio.edu) or the Co-investigator: Salayna Hritz (s.hritz@vikes.csuohio.edu).

Link to Survey:
https://psyhscsu.iad1.qualtrics.com/jfe/form/SV_23jex5nbaCDUNqS

APPENDIX C

Informed Consent Form: Research Match and Social Media Version

Department of Psychology

COLLEGE OF SCIENCES AND HEALTH PROFESSIONS

Description of Research Study

This research study is a part of Salayna Abdallah's master's thesis for Cleveland State University. The primary investigator (PI) is Dr. Amir Poreh of the Psychology Department of Cleveland State University. For this study, you will be asked to complete 81-items in a questionnaire and a facial affect recognition portion which will determine the accuracy of a new scale for detecting autism spectrum disorder (ASD). This study should take approximately 25 minutes to complete. We hope to develop a new ASD scale which may be more effective than self-report surveys that are currently used to diagnose ASD.

Risks

At risk is the inconvenience of taking the time to participate in the study. Additionally, at risk is the accidental disclosure of personal information. You may also experience some frustration while completing questionnaires. If you experience an issue, you should call 211, or use the web site http://www.211.org. This web site will help you find mental health agencies in your area. For immediate help, you should text 'HOME' to 741741 and connect with a counselor or go to the nearest emergency room. You may choose not to answer any question if you wish to discontinue. You may end the study with no consequence. There is a risk that someone will enter our system and see your email address. We will do everything we can to keep your answers safe. We will also remove your email address from the data. This is to ensure the confidentiality of your answers. Your answers will be stored on a password-protected USB drive in a locked cabinet. Your answers may be used for further research, but you will not be identifiable.

Benefits

There are no guaranteed direct benefits for participating in this study. A possible benefit is being part of a research study that created a new scale for diagnosing ASD. If this scale is useful, it may be published and used for diagnosing ASD in the future. This research study will not involve direct compensation. This study will consist only of individuals who wish to volunteer. Although, volunteers are eligible to participate in a random drawing for five $5 Amazon gift cards. There is about 1% chance you will win a card. If you win the card, we will email you a link via Amazon.com to receive the card.

Privacy

Your answers to the questions will be kept private. The data will be collected on a HIPAA compliant website. It will later be kept on a password protected hard drive. Your name will never appear, but your email will be kept in our system. When the study is

complete, your email will be removed. You will not be identified in any way in this study. You will also not be identified in any other study if your file is shared with other researchers. You can contact the PI if you decide you do not want your data to be used. You can use the phone numbers or email listed below to find who to contact. We do not expect a breach in confidentiality. If confidentiality is broken, your email could be associated with your participation in this study. However, your email will not be connected to your answers. If your answers are identified, they cannot be identified as yours.

Conflict of Interest

There are no conflicts of interest to report.

Questions

If you have any questions or concerns, please contact Dr. Amir Poreh at (216) 687-3718 or a.poreh@csuohio.edu or Salayna Abdallah at s.hritz@vikes.csuohio.edu. Taking part in this study is completely up to you. You may choose not to take part or may leave the study at any time with no penalty. Please read the following: "I understand that if I have any questions about my rights as a research subject, I can contact the Cleveland State University Institutional Review Board at (216) 687-3630.

I am 18 years or older and have read and understand this consent form and agree to participate.

- ○ I agree to participate (1)
- ○ I do not agree to participate (2)

APPENDIX D

Informed Consent Form: Cleveland State University (CSU) Participant Version

Department of Psychology

COLLEGE OF SCIENCES AND HEALTH PROFESSIONS

Description of Research Study

This research study is a part of Salayna Abdallah's master's thesis for Cleveland State University. The primary investigator (PI) is Dr. Amir Poreh of the Psychology Department of Cleveland State University. For this study, you will be asked to complete 81-items in a questionnaire and a facial affect recognition portion which will determine the accuracy of a new scale for detecting autism spectrum disorder (ASD). This study should take approximately 25 minutes to complete. We hope to develop a new ASD scale which may be more effective than self-report surveys that are currently used to diagnose ASD.

Risks

At risk is the inconvenience of taking the time to participate in the study. Additionally, at risk is the accidental disclosure of personal information. You may also experience some frustration while completing questionnaires. If you experience an issue, you should call 211, or use the web site http://www.211.org. This web site will help you find mental health agencies in your area. For immediate help, you should text 'HOME' to 741741 and connect with a counselor or go to the nearest emergency room. You may choose not to answer any question if you wish to discontinue. You may end the study with no consequence. There is a risk that someone will enter our system and see your email address. We will do everything we can to keep your answers safe. We will also remove your email address from the data. This is to ensure the confidentiality of your answers. Your answers will be stored on a password-protected USB drive in a locked cabinet. Your answers may be used for further research, but you will not be identifiable.

Benefits

There are no guaranteed direct benefits for participating in this study. A possible benefit is being part of a research study that created a new scale for diagnosing ASD. If this scale is useful, it may be published and used for diagnosing ASD in the future.

Privacy

Your answers to the questions will be kept private. The data will be collected on a HIPAA complaint website. It will later be kept on a password protected hard drive. Your name will never appear, but your email will be kept in our system. When the study is complete, your email will be removed. You will not be identified in any way in this study. You will also not be identified in any other study if your file is shared with other researchers. You can contact the PI if you decide you do not want your data to be used.

You can use the phone numbers or email listed below to find who to contact. We do not expect a breach in confidentiality. If confidentiality is broken, your email could be associated with your participation in this study. However, your email will not be connected to your answers. If your answers are identified, they cannot be identified as yours.

Conflict of Interest

There are no conflicts of interest to report.

Questions

If you have any questions or concerns, please contact Dr. Amir Poreh at (216) 687-3718 or a.poreh@csuohio.edu or Salayna Abdallah at s.hritz@vikes.csuohio.edu. Taking part in this study is completely up to you. You may choose not to take part or may leave the study at any time with no penalty. Please read the following: "I understand that if I have any questions about my rights as a research subject, I can contact the Cleveland State University Institutional Review Board at (216) 687-3630.

Other SONA Info

I acknowledge that I am participating in this study in order to learn about psychological research beyond what is presently in my lectures and textbook. I acknowledge that there is an alternative option for receiving research/experiment credits. The alternative is completing a series of short papers (e.g., 1-2pages) on some topics in research. I am aware that I able to use a combination of research participation and short papers. Therefore, I acknowledge that I am choosing to participate in this research study for part of my research/experiment credit to receive .5 credits as compensation.

I am 18 years or older and have read and understand this consent form and agree to participate.

- ○ I agree to participate (1)
- ○ I do not agree to participate (2)

APPENDIX E

Demographic Survey

Q1 Age

_____

Q2 Gender

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

Q3 Ethnicity

- ○ American Indian or Alaska Native (1)
- ○ African American (2)
- ○ Asian American (3)
- ○ Hispanic/Latino American (4)
- ○ Native Hawaiian or Other Pacific Islander (5)
- ○ White (6)
- ○ Other (7) _____

Q4 Level of Education

- ○ Some high school (1)
- ○ High school graduate (2)
- ○ Some college (3)
- ○ Associate's degree (4)
- ○ Bachelor's degree (5)
- ○ Master's Degree (6)
- ○ Doctorate Degree (7)

Q5 Are you currently diagnosed with autism spectrum condition(s)? Or do you suspect you might have ASC?

- ○ Yes (1)
- ○ No (2)

Display This Question:

If Are you currently diagnosed with autism spectrum condition(s)? Or do you suspect you might have ASC? = Yes

Q6 Who made the diagnosis?

- ○ Self (1)
- ○ Psychiatrist (2)
- ○ Primary Care Physician (3)
- ○ Nurse Practitioner (4)
- ○ Psychologist (5)
- ○ Social Worker (6)
- ○ Psychiatrist (7)

Q9 Have you been treated for any of the following mental health conditions?

- [ ] Anxiety (1)
- [ ] Post-Traumatic Stress Disorder (PTSD) (2)
- [ ] Obsessive Compulsive Disorder (OCD) (3)
- [ ] Social Phobia (4)
- [ ] Depression (5)
- [ ] Bipolar Disorder (6)
- [ ] Schizophrenia (7)
- [ ] Schizotypal Personality Disorder (8)
- [ ] Anti-Social Personality Disorder (9)
- [ ] Avoidant Personality Disorder (10)
- [ ] Obsessive-compulsive Personality Disorder (11)
- [ ] Borderline Personality Disorder (12)
- [ ] Street Drugs Use (Cocaine/Opiates) (13)
- [ ] Alcohol related disorder (abuse or dependence) (14)
- [ ] Medically unexplained physical symptoms (15)
- [ ] Hypochondriasis or Somatoform Disorder (16)
- [ ] Eating disorder(s) (17)
- [ ] Attention Deficit Hyperactivity Disorder (ADHD) (18)

☐ Other (19) _____

☐ I have NOT been diagnosed/treated for any of the following mental health conditions. (20)

Display This Question:

If Are you currently diagnosed with autism spectrum condition(s)? Or do you suspect you might have ASC? = Yes

Q11 Are you taking any medication for any of the above mental health problems?

○ Yes (1)

○ No (2)

Display This Question:

If Are you taking any medication for any of the above mental health problems? = Yes

Q12 Who prescribed the medication?

○ Primary Care Physician (1)

○ Psychiatrist (2)

○ Nurse Practitioner (3)

Q13 Psychotropic Medications

- [ ] REXULTI Brexpiprazole:Right (1)
- [ ] Auvelity (bupropion and dextromethorphan):Right (2)
- [ ] Modafinil Provigil:Right (3)
- [ ] Atomoxetine (Strattera):Right (4)
- [ ] Atomoxetine (Strattera):Right (5)
- [ ] Invega (Paliperidone):Right (6)
- [ ] Invega (Paliperidone):Right (7)
- [ ] Benzatropine (Cogentin):Right (8)
- [ ] Nefazodone (MAO):Right (9)
- [ ] Ritalin (methylphenidate):Right (10)
- [ ] Dexedrine (dextroamphetamine):Right (11)
- [ ] Tranxene (clorazepate):Right (12)
- [ ] Tenormin (atenolol):Right (13)
- [ ] Inderal (propranolol):Right (14)
- [ ] Asendin (amoxapine):Right (15)
- [ ] Parnate (tranylcypromine):Right (16)
- [ ] Nardil (phenelzine):Right (17)
- [ ] Marplan (isocarboxazid):Right (18)

- [ ] Zyprexa (olanzapine):Right (19)
- [ ] Risperdal (risperidone):Right (20)
- [ ] Geodon (ziprasidone):Right (21)
- [ ] Clozaril (clozapine):Right (22)
- [ ] Haldol (haloperidol):Right (23)
- [ ] Stelazine (trifluoperazine):Right (24)
- [ ] Trilafon (perphenazine):Right (25)
- [ ] Thorazine (chlorpromazine):Right (26)
- [ ] Seroquel (quetiapine):Right (27)
- [ ] Adderall (amphetamine and dextroamphetamine):Right (28)
- [ ] Latuda (Lurasidone):Right (29)
- [ ] Viibryn (Vilazodone):Right (30)
- [ ] Gabapentin (Neurontin Neuraptine Gralise):Right (31)
- [ ] Omeprazole for GERD:Right (32)
- [ ] Primidone for Parkinson:Right (33)
- [ ] Topirimate (Topamax):Right (34)
- [ ] Abilify (aripiprazole):Right (36)
- [ ] Pristiq (Desvenlafaxine):Right (37)

- [ ] Mirtazapine (Remeron):Right (38)
- [ ] Trazodone HCL (Desyrel):Right (39)
- [ ] Vyvanse (Lisdexamfetamine):Right (40)
- [ ] Sycrest (Saphris):Right (41)
- [ ] Depakote or Epilim (Sodium valproate):Right (42)
- [ ] Lamictal (Lamotrigine):Right (43)
- [ ] Tegretol (Carbamazepine):Right (44)
- [ ] Lithium (Eskalith):Right (45)
- [ ] Lyrica (Pregabalin):Right (46)
- [ ] BuSpar (buspirone):Right (47)
- [ ] Cymbalta (duloxetine) DI or RI:Right (48)
- [ ] Celexa (citalopram):Right (49)
- [ ] Lexapro (escitalopram):Right (50)
- [ ] Paxil (paroxetine):Right (51)
- [ ] Zoloft (sertraline):Right (52)
- [ ] Luvox (fluvoxamine):Right (53)
- [ ] Prozac (fluoxetine):Right (54)
- [ ] Anafranil (clomipramine):Right (55)

- [ ] Doxepin (Sinequan or Adapin):Right (56)
- [ ] Elavil (amitriptyline):Right (57)
- [ ] Aventyl or Pamelor:Right (58)
- [ ] Norpramin (desipramine) Pertofrane:Right (59)
- [ ] Tofranil (imipramine):Right (60)
- [ ] Librium (chlordiazepoxide):Right (61)
- [ ] Serax (oxazepam):Right (62)
- [ ] Valium (diazepam):Right (63)
- [ ] Ativan (lorazepam):Right (64)
- [ ] Xanax (alprazolam):Right (65)
- [ ] Klonopin (clonazepam):Right (66)
- [ ] Emsam (selegiline):Right (67)
- [ ] Trintellix (Vortioxetine):Right (68)
- [ ] Fetzima (Levomilnacipran):Right (69)
- [ ] Prestiq (Desvenlafaxine):Right (70)
- [ ] Effexor (venlafaxine):Right (71)
- [ ] Viibryd (Vilazodone):Right (72)
- [ ] Wellbutrin SR (Bupropion):Right (73)

☐ Wellbutrin IR (Bupropion):Right (74)

☐ Fluoxetine (Prozac):Right (75)

☐ Other (76) _____

Display This Question:

If Are you taking any medication for any of the above mental health problems? = Yes

Q13 Do you find that the current medication you are taking is helpful?

○ Yes (1)

○ No (2)

APPENDIX F

Debrief Form

Department of Psychology

COLLEGE OF SCIENCES AND HEALTH PROFESSIONS

Thank you for your participation in our research study. Our goal in this study was to assess the ability of a new self-report measure to detect Autism Spectrum Disorder (ASD) symptoms. We hope to develop a new ASD scale which may be more effective than self-report surveys that are currently used to diagnose ASD.

We did this by including three experimental groups. The first group was composed of individuals who reported having a history of ASD. This study is not concerned with the legitimacy of ASD symptoms among those who have a history of ASD. Subjects with a history of ASD serve as the experimental 'gold standard' legitimate group, which other groups are compared to. The second group was composed of individuals with a history of depression and anxiety. The third group was composed of individuals with no mental health history. Each group took the same tests so that the degree of difference in their scores could be ascertained and used for analysis.

Thank you again for participating in our study. Please email Salayna Abdallah: s.abdallah@vikes.csuohio.edu with any questions.