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Personality Matters: Treatment Outcomes in Different Personality Subgroups of Children with Autism Spectrum Disorder

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Personality Matters: Treatment Outcomes in Different Personality Subgroups of Children with Autism Spectrum Disorder

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ABSTRACT OF THE THESIS

Personality Matters: Treatment Outcomes in Different Personality Subgroups

of Children with Autism Spectrum Disorder

by

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Master of Arts in Education

University of California, Los Angeles, 2020

Professor Jeffrey J. Wood, Chair

Autism spectrum disorder (ASD) has been identified as a heterogeneous disorder with multiple syndromes and etiologies (Tordjman et al., 2017). The current literature has yet to identify valid subgroups with key distinct features in the ASD population that can contribute further insights into the disorder. By taking a bottom-up approach in observing trait differences within ASD through the lens of personality profiles, it is possible that homogeneous subgroups may be identified. Thus, the present study aimed to identify possible personality subgroups within school-aged children in the ASD population, and to evaluate potential differences in treatment outcomes between these subgroups as one mechanism for assessing the predictive validity of the subgroups. Data from a CBT treatment multi-site RCT with school-aged children (*N*=213; ages 7 – 13 years old) were used. Latent profile analysis of the participants' personality measure scores revealed a 5-class solution that best fit the data. Omnibus ANCOVAs identified significant differences between the five identified personality subgroups on the Child Anxiety Impact Scale (CAIS; Langley et al., 2014) treatment outcome scores, after controlling for pre-treatment scores. Furthermore, specific contrasts revealed that personality subgroup response to CBT treatment for anxiety was also contingent on the type of treatment each individual received. One subgroup (Group 1) responded better to a particular treatment condition (Standard-of-Practice CBT), while another subgroup (Group 2) responded better to the other treatment condition (Adapted CBT). Exploratory analyses and implications are discussed.

The thesis of An Chuen Cho has been approved.

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2020

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Background

Autism spectrum disorder (ASD) is a neurodevelopmental disorder characterized by persistent deficits in social communication and interaction, as well as restrictive, repetitive behaviors (American Psychiatric Association, 2013). It is currently estimated that 1 in 59 children in the United States are diagnosed with ASD (Baio et al., 2018). Even though comprehensive diagnostic criteria for ASD can be found in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), there remains a great deal of variability in the expression and severity of these symptoms across individuals with ASD (Masi et al., 2017). Given this heterogeneity, ASD is considered a broad clinical diagnosis that consists of multiple separable syndromes (Tordjman et al., 2017). This “multiple autisms” model highlights the phenotypic variability within the ASD population, which has emerged as a challenge in better understanding the different presentations of the disorder and their possible etiological causes. Unfortunately, research has yet to reveal valid ASD subtypes with distinct characteristics and underpinnings (Grzadzinski et al., 2013).

Heterogeneity in Autism Spectrum Disorder

Autism is described as a “spectrum disorder” due to the heterogeneity of symptoms and severity level that individuals experience (Jeste & Geschwind, 2014; Masi et al., 2017; Tordjman et al., 2017). For some, an ASD diagnosis describes serious challenges with language usage, attention allocation, and accompanying intellectual disability. And for others, for example, it is a diagnosis that encompasses difficulties in forming social relationships as well as comorbid symptoms of emotion dysregulation. Within the ASD population, there is a great deal of variability in individuals' symptom severity (e.g., ability to change communication to match context, ability to make social inferences, ability to form meaningful social relationships, rigidity in behavior), verbal and intellectual ability, and comorbid symptoms (Masi et al., 2017). The "multiple autisms" model denotes the likelihood of various presentations of ASD and suggests that homogeneous subgroups within the ASD population represent distinct subtypes of autism and are more likely to share etiological causes, have more similar past and current clinical features, and may be on a more similar life trajectory in terms of issues such as adaptive outcomes (job, relationships), concurrent mental health risk (disorders, need for treatment and higher levels of care), and quality of life. For example, it may be possible that individuals with memberships in differing autism subtypes present differential response to treatments for core autism symptoms and comorbid clinical features. Thus, the identification of autism subtypes plays a crucial role in understanding the differences across various develop mental and clinical domains.

The current genetics literature highlights autism's heterogeneity. ASD has proven to exhibit high heritability – the relative recurrent risk (RRR) for monozygotic twins, dizygotic twins, and full siblings is estimated to be 153.0, 8.2, and 3.3, respectively (Sandin et al., 2014). However, identified susceptibility genes have varied in function, although all seem to be associated with pathways related to neuronal and synaptic homeostasis (Huguet et al., 2013). Recent findings also suggest that environmental influences play a significant role in the pathogenesis of ASD (Hallmayer et al., 2011; Tick et al., 2016), and as such, the gene-environment interaction serves as an additional risk factor associated with ASD etiology (Kim & Leventhal, 2015). The "multiple autisms" model is grounded in the genetics literature in that various polygenic risk models, in combination with environmental effects, surpasses the risk threshold that results in the clinical presentation of ASD (de la Torre-Ubieta et al., 2016). Nonetheless, given the heterogeneity in genetic profiles and phenotypic expressions within autism, research has yet to disentangle the different possible syndromes that exist within the ASD diagnosis (Grzadzinski et al., 2013).

Relevant research has been conducted on various levels (brain anatomy and physiology: Sivapalan & Aitchison, 2014; genetics: De Rubeis & Buxbaum, 2015), and while these studies have reaffirmed the heterogeneous nature of ASD, homogeneous subgroups with key identifiable features remain elusive. In line with the "multiple autisms" model, which suggests differential levels of neuronal under-connectivity (Hoppenbrouwers et al., 2014), a recent review of neurological and structural findings reaffirmed that notable abnormalities in neural networks and brain structure exists between those with autism and those without (Sivapalan & Aitchison, 2014). However, despite a few trends found in the literature, no conclusive evidence can be established regarding the heterogeneous presentation of those with ASD.

In a genetics literature review by De Rubeis and Buxbaum (2015), deep phenotyping studies of disrupted genes (namely, the *CHD8* and *ADNP* genes) have proposed potential ASD subtypes, but the sampling from phenotypes of interest introduces a bias that has yet to be accounted for. As such, although a genotype-first approach has yielded promising preliminary findings (see: Stessman et al., 2014), it seems that research grounded in the phenotypic presentations (i.e., predispositions and behaviors) of individuals with ASD is required to fully understand the variability and complexity of the "multiple autisms". The aforementioned reviews illustrate the predicament of heterogeneity research within the autism field. That is, although the scientific community has been able to identify the heterogeneity that exists within the ASD population, there remains a dearth of research that can identify meaningful, homogeneous subgroups amongst those with ASD.

Evaluating Autism Spectrum Disorder from A Personality Context

An often-overlooked perspective in identifying subgroups within populations of interest is the lens of personality variability. The current literature has shown that personality: (1) is the product of the perpetual exchange between one's genetic predispositions and environmental influences (Briley & Tucker-Drob, 2014), (2) can explain both normal and maladaptive thoughts and behaviors (Lee & Ashton, 2014), and (3) remains relatively stable (Borghuis et al., 2017). In other words, one's predispositions and interaction with their daily environment can be partly described as a phenotypic expression of their personality. As such, by better understanding the personality variability within a population of interest, it may be possible to elucidate the primary behavioral characteristics that unify the various subgroups represented within a particular clinical diagnosis, as well as the subgroups' symptomatology and life trajectories. This approach seems particularly promising in evaluating the subtypes captured within the "multiple autisms" model in ASD research.

Among many different personality frameworks, a traditional approach to analyzing personality is the five-factor model of personality (FFM; also known as the "Big Five") by Costa and McCrae (1992). Utilizing factor analysis, the model suggests that five broad dimensions can be used to fully encompass the major themes of the human personality and psyche. This empirical model has been considered as a useful framework for psychopathology research because it can capture both normative and abnormal personality traits (DeYoung, 2015). The five factors include: (1) Openness to Experience (e.g. "I like to create new games and entertainments", "I would like very much to travel and to know the habits of other countries"),

(2) Conscientiousness (e.g. "I like to keep all my school things in order", "I play only when I have finished my homework"), (3) Extraversion (e.g. "I like to joke", "I easily make friends"), (4) Agreeableness (e.g. "If someone commits an injustice towards me, I forgive that person", "I trust others"), and (5) Neuroticism (e.g. "I easily get angry", "I am sad"). In the traditional application of the FFM, each factor comprises six facets (sub-traits) that can be assessed independently of the trait they belong to (Costa & McCrae, 1992). For example, Sensation-Seeking Behavior and Assertiveness are two facets that fall under the factor category of extraversion. When used to study personality disorders, the FFM has been shown to substantially map onto personality disorders as characterized by the Personality Inventory for the DSM-5 (PID-5) (DeYoung et al., 2016; Gore & Widiger, 2013).

Perhaps the best example highlighting the application of the FFM framework to identify subtypes with differing developmental origins comes from psychopathy research. The triarchic model of psychopathy proposed in a review by Patrick and Drislane identifies three distinct phenotypic constructs that contribute to the formation of a psychopathic personality: disinhibition, meanness, and boldness (2015). According to this model, the clinical diagnosis of psychopathy is a result of either a disposition towards disinhibition or boldness, and these two distinct etiological pathways are primarily driven by their own risk factors (i.e., an emotional/fearful temperament or, conversely, a fearless temperament). This model helps resolve the disparate findings between competing conceptions of psychopathy that either emphasized an individual's rage and lack of control, or, conversely, their cold-blooded, calculated, and emotionless disregard for others' rights and feelings. The three personality constructs identified in the model are primarily reflected as such in the FFM: disinhibition as low conscientiousness, meanness as low agreeableness, and boldness as high extraversion and low neuroticism. The neurobiological underpinnings of these two differing pathways to a final common taxon of psychopathy have been well documented over the past 20 years. This body of research serves as an exemplar in analyzing a psychopathology construct with a personality lens in order to elucidate the traits of multiple “subtypes” of the same heterogeneous “clinical disorder”.

In the same vein, it can be argued that variability in personality maps onto the diagnostic criteria of ASD very well. Consequently, the deficits and maladaptive behaviors characterized as the core symptoms of ASD, as well as its comorbid symptoms, can be accounted for or at least described by trait-based differences in personality profiles when compared to the general population. Past studies suggest that there is a strong relationship between personality and ASD, and personality research may serve as an empirical approach in identifying behavioral subgroups within ASD (Lodi-Smith et al., 2018; Vuijk et al., 2018). Conceptual overlaps between personality research and ASD research have consistently appeared across various symptom domains, but none have been explicitly highlighted. For example, individuals with high Autism-Spectrum Quotient (AQ; Baron-Cohen & Wheelwright, 2001) scores were found to have higher emotional reactivity and lower endurance, which are reflective of high neuroticism and low conscientiousness, respectively (Pisula et al., 2015). Similarly, low social motivation is a common characteristic associated with ASD, which has demonstrated a significant relationship with low extraversion (Epstein & Silbergsweig, 2015; Kelsen & Liang, 2018).

Despite this notion, very few studies have attempted to explain the heterogeneity within the ASD population using personality subgroups. Schriber and colleagues (2014) found that individuals with ASD were more neurotic and less extraverted, agreeable, conscientious, and open to experience than typically-developing peers. However, in that study, the results showed that these five personality traits failed to predict within-group variability in ASD symptom severity. Schwartzman and colleagues (2015) administered both a personality questionnaire (IPIP-NEO-120; Johnson, 2014) and an autism trait questionnaire (RAADS-R; Ritvo et al., 2011) to 828 adults recruited via the internet and ASD social networks. The study found that personality facets from the five-factor model of personality accounted for 70% of the variance in autism trait scores and that autism symptom severity was positively correlated with neuroticism and negatively correlated to extraversion, agreeableness, conscientiousness, and openness to experience. Four personality subgroups were identified: (1) distinctly high anxiety, self-consciousness, and vulnerability scores, (2) high Neuroticism, very low Conscientiousness, and low Agreeableness scores (characteristic of someone with borderline personality disorder), (3) average facet scores in Neuroticism and Conscientiousness, but low in Extraversion and Agreeableness, and (4) a relatively normative profile with all factor and facet scores within one standard deviation of the mean. This suggests that the phenotypic profiles of individuals with ASD may be partially explained by their personality traits; furthermore, one may be able to better understand patterns of individual variability, or subgroups within ASD, through the application of a person-centered approach to personality trait profiles. Left largely unanswered in this study is whether the identified subgroups have distinctive etiologies and differential future life trajectories. More research needs to be conducted to determine whether developmentally and empirically meaningful personality subgroups can be identified in the ASD population.

Identifying Subgroups via Latent Profile Analysis

While there are several ways to extrapolate subgroups from quantitative data, such as an array of personality trait scores in the FFM framework, an effective manner of doing so is utilizing a finite mixture model such as latent profile analysis (LPA; Gibson, 1959; Miettunen et al., 2016). LPA is a subset of structural equation modeling used to find groups or subtypes of cases in multivariate continuous data. This statistical method attempts to detect the presence of latent classes, having the benefit of recognizing unobservable subgroups that are not immediately apparent, even with thorough inspection of the collected data (e.g., organization and grouping by similarities and/or differences within manifest variables). LPA can also be used to classify cases according to their “maximum likelihood class membership”. Essentially, a successful LPA model is able to classify individual participants in a sample into separable and homogeneous empirically identified subgroups – a key current goal in ASD research.

One advantage of LPA as opposed to older methods such as cluster analysis is that it is a more empirically stringent method. LPA identifies latent subgroups using a probabilistic model that describes the data distribution, whereas cluster analysis simply finds similarities between cases and creates clusters given an arbitrarily chosen distance measure. LPA, and its categorical variable-equivalent LCA (latent class analysis), has been used to identify subgroups in many different populations of interest, including the social anxiety disorder population (Peyre et al., 2016), the postpartum depression population (PACT Consortium, 2015), the posttraumatic stress disorder (PTSD) population (Galatzer-Levy et al., 2013), as well as the schizophrenia population (Tsai & Rosenheck, 2013).

For example, in a study by Peyre and colleagues (2016), latent modeling was used to observe the relationship between social anxiety disorder (SAD) and quality of life outcomes. Results found four latent classes among the US nationally representative sample with a lifetime diagnosis of SAD: generalized severe (15%), generalized moderate (43%), generalized low (18%), and performance only (24%). For the three generalized subgroups, it was revealed that as number of social situations feared increases, mental health comorbidity increases and quality of life decreases. Additionally, although those in the “performance only” subgroup shared significantly more feared social situations, this subgroup presented better mental health outcomes, suggesting that performance anxiety may perhaps be a variant of generalized anxiety disorder with unique symptomatology and etiology. These categorical differences and implications would not be visible without the use of LPA. However, in autism research, there has yet to be any studies that utilize LPA in attempt to classify possible personality subgroups in the ASD population. Thus, an important next step within autism research is to apply LPA models to identify latent subgroups that may exist within the ASD population.

Predicting Treatment Response as A Measure of Subgroups' Predictive Validity

An essential component of classifying valid subgroups within the ASD population is determining whether or not the subgroups present meaningful differences beyond the present. The subgroups' predictive validity is the extent in which these subgroups not only reflect differences in symptom expression and severity level, but also demonstrate profiles with distinct developmental patterns and future outcomes. In other words, identified subgroups are most meaningful with substantial predictive validity, as they can categorize individuals not just at a specific given time, but rather have implications for future trajectories and response to life contexts.

Treatment response is a strong indicator of predictive validity as it captures one's sensitivity to treatment and capacity to improve in ability (e.g., social engagement, executive functioning) and reduce unwanted symptoms (e.g., anxiety, inappropriate social behavior). As an example of measuring treatment response in individuals with ASD, a randomized, controlled trial study by Wood and colleagues (under review) tested the efficacy of a cognitive-behavioral therapy (CBT) intervention that targets anxiety and was adapted for the characteristics of ASD. The efficacy of CBT for school-aged youth with ASD and comorbid clinical anxiety has been well studied, demonstrating effects that are comparable to CBT interventions for typically-developing youth with clinical anxiety. While the study findings revealed that an adapted CBT approach is beneficial to youth with ASD and clinical anxiety in reducing anxiety symptoms, the study did not identify subgroups within their sample. The present study utilized secondary data from this intervention study to identify subgroups and compared their treatment response to examine the subgroups' predictive validity.

A Gap in the Literature

The previous research on personality and ASD has laid a foundation for the identification of subgroups in the ASD population. Notably, the study by Schwartzman and colleagues (2015) identified personality subgroups within a sample of adults with ASD. However, outside of this one study, no known studies have attempted to identify personality subgroups among those with ASD, and there is no evidence that these subgroups exist in children with ASD. Furthermore, research has yet to identify ASD subgroups that predict future trajectories (e.g., differences in treatment response), which may have implications for maximizing child benefits and minimizing costs. As such, there remains a gap in the literature for reasoning whether possible personality-based subgroups in the ASD population have meaningful differences that elucidate differential etiologies, current clinical profiles, and future life trajectories within the autism spectrum. Therefore, the present study aimed to:

Research Aim 1: Identify possible different personality subgroups within school-aged children in the ASD population.

Hypothesis 1: Distinct personality subgroups of children with ASD will be identified that resemble the subgroups identified in adults with ASD by Schwartzman and colleagues (2016).

Research Aim 2: Evaluate the predictive validity of the identified personality subgroups in children with ASD by examining whether there are differences in CBT treatment outcomes among the children classified into the identified personality subgroups.

Hypothesis 2: Some subgroups of children with ASD will demonstrate better CBT treatment response when compared to other subgroups.

Methods

Participants

The current study used data from a three-site randomized, controlled trial (RCT) which concluded in 2017 (Wood et al., under review). The RCT compared an Adapted CBT treatment designed for children with a comorbid presentation of ASD and anxiety (Behavioral Interventions for Anxiety in Children with Autism (BIACA); Wood & Wood, 2013), referred to here as Adapted CBT, to a Standard-of-Practice CBT treatment for anxiety (Coping Cat; Kendall, 2006) and to treatment-as-usual (TAU). The study screened 213 children (ages 7 to 13 years old) with high-functioning autism for the RCT and were recruited through via flyers, letters/emails, and referrals from local clinics and medical centers. Children were eligible for Screening if they carried a clinical diagnosis of ASD from a qualified provider, if parents reported they had verbal communication ability, and if they were between the ages of 7 and 13 years. After Screening measures were administered, children were eligible for the RCT if they met the following inclusion criteria: (a) met research criteria for a diagnosis of autism, based on the child's Childhood Autism Rating Scale (CARS; Schopler et al., 2010) and Autism Diagnostic Observation Schedule (ADOS-2; Lord et al., 2012) scores, (b) have clinically significant anxiety (i.e., a severity score greater or equal to 14 on the Pediatric Anxiety Rating Scale [PARS;

Research Units on Pediatric Psychopharmacology Anxiety Study Group (RUPP), 2002; see below]), (c) had an estimated full-scale IQ > 70, computed from the Vocabulary and Matrix Reasoning subscales in the Wechsler Intelligence Scale for Children – Fourth Edition (WISC-IV; Wechsler, 2003), (d) if taking psychotropic medication, maintained a stable dose for at least 4 weeks prior to baseline assessment with no plan of changes during the treatment period and (e) not partaking in concurrent behavioral interventions (e.g., applied behavioral analysis) that required an extensive time commitment or psychotherapy that targeted anxiety. These criteria were set to establish the study's internal validity, as well as to guarantee participants would have access to all the intervention's components. For example, the IQ score inclusion criterion assures that participants in the study have the cognitive capability to fully engage in and receive the benefits of the intervention.

Table 1 presents descriptive and diagnostic information for the present study's sample. Of the 213 children that were screened, only 202 had sufficient HiPIC data to be used for further analyses. There were 76, 72, and 19 participants in the Adapted CBT, Standard-of-Practice CBT, and TAU conditions, respectively, totaling to 167 participants that were assigned a treatment condition as part of the intervention. Within each condition, two participants were missing HiPIC data. As such, the present study has a sample of 202 participants, in which 161 participants were assigned a treatment condition (Adapted CBT, $n = 74$; Standard-of-Practice CBT, $n = 70$; TAU, $n = 17$).

Study Treatment and Assessments

After the participants were screened, each eligible child was randomized to receive either the Standard-of-Practice CBT (Coping Cat), Adapted CBT (BIACA), or "treatment-as-usual" (TAU). The computer-generated randomization stratified based on treatment site, verbal IQ (≥90 vs. <90), and ADOS score, which ensured an appropriate sample size with similar group compositions on variables that may have an effect on treatment outcome. Both diagnosticians and families were blind to the participants' CBT treatment conditions to address expectancy effects.

Adapted cognitive-behavioral therapy (BIACA). In the Adapted CBT condition, participants had 16 weekly therapy sessions based on the CBT manual for children with ASD (Behavioral Interventions for Anxiety in Children with Autism; Wood et al., 2013). The intervention program is a compendium of evidence-based practices for school-aged youth with ASD and contains various modules that address anxiety as well as some core ASD symptom areas. In this intervention, the therapist and family work together to encourage the participant to face fears and use pro-social behaviors across settings (e.g., home, school, community). Each session lasted 90 minutes, with 45 minutes dedicated solely to the child and 45 minutes allotted to working with the parents or entire family together.

The primary mechanism which underlies this Adapted CBT condition is exposure therapy, a psychological technique which creates a safe environment to expose to participants fearful or anxiety-inducing stimuli with the goal of reducing fear and decreasing avoidance. Exposure therapy is central to the structure of the Adapted CBT condition and historically has proven to be effective in treating various anxiety disorders (Kaczkurkin & Foa, 2015). Additionally, the intervention utilizes a personalized, modular format and reward system to implement both long-term and short-term goals that target the development of coping skills, pro-social behavior and reduction of anxiety and restricted and repetitive behaviors. Concepts are taught via multimodal stimuli (e.g., telling stories, drawing cartoons) and guided Socratic questioning, in which thoughts and questions were utilized to deconstruct and better understand said concepts.

Standard-of-Practice cognitive-behavioral therapy (Coping Cat). In the Standard-of-Practice CBT condition, the participants met with a trained interventionist for 16 weekly 60-minute sessions that represented the contemporary established approach of CBT for child anxiety. This intervention has proven effective across various prior trials (Lenz, 2015). The first eight sessions are designed to educate the child on skills and concepts, while the final eight sessions provide an opportunity for the child to utilize the newly learned skills and techniques through exposure tasks during sessions and assigned homework between sessions. This intervention aims to teach youth to recognize unwanted, anxious feelings and then to utilize these feelings as cues to execute anxiety management strategies. This process is highlighted by five features: (a) recognition of anxious feelings and related somatic reactions, (b) cognitive awareness of resulting negative thoughts or expectations, (c) establishing alternative mental plans to cope with situations, (d) practice in behavioral exposure tasks, and (e) exercising self-evaluation and self-reinforcement. Behavioral strategies include modeling, imaginal and in-vivo exposure tasks, role-playing, and contingent reinforcement.

Parent involvement is limited to a weekly 15-minute check-in during the start of each session, as well as three meetings between the parents and the interventionist over the treatment period. Parents may also be asked to participate in the child's exposure tasks and homework assignments between sessions. In addition, parents are given a pamphlet that outlines their child's treatment as well as their potential contributions to their child's outcome.

Treatment-as-usual (TAU). Families in the TAU condition were provided with a standard list of various clinical (community, specialty, private practice) referrals for both individual and group child psychotherapy at each RCT site. Specific recommendations were not provided, and families were responsible for choosing (or not choosing) any treatment approach they wished to try for three months while in the TAU condition. In the RCT, only 12 of the 17 children in the TAU condition received psychological or psychiatric care (see Wood et al., under review). Given the heterogeneity among the treatments received (or lack thereof) by those in the TAU condition, the present study excluded these cases when comparing differences in treatment outcomes related to personality scores (i.e., omnibus ANCOVA and specific contrasts, regression analyses).

Evidence-based assessments. Parents and children participated in evidence-based assessments prior to randomization and at the end of treatment (post-treatment assessment). These assessments took approximately three hours. Assessments were carried out by independent evaluators who were blind to the participants' treatment conditions. Measures relevant to the current study are described in detail below.

Measures

Hierarchical Personality Inventory for Children (HiPIC). The HiPIC (Mervielde & De Fruyt, 1999) is a parent-reported personality measure that is based on the five-factor model of personality (FFM). The HiPIC was conducted during the screening assessment. The 144 items in the questionnaire are grouped into 18 facets, hierarchically organized under the five FFM higher-order factors. For each item, parents were instructed to indicate the degree to which the statement characterizes their child's behavior over the past year. A 5-point Likert-type scale was used, ranging from "barely characteristic" (1) to "highly characteristic" (5). The questionnaire items all share a similar grammatical format and take on a third-person singular perspective, with intent to avoid negations in the items and exclude personality-descriptive adjectives (i.e., words used to describe individuals, such as “lazy” or “angry”, are not used in the items’ sentence structure). Collected item response scores can be tabulated to generate a personality profile (both on the factor and facet levels) for each participant. Using the data from a large comparison group, raw scores on the HiPIC facet and factor scale can be converted into gender and aged-normed decile scores that reflect an individual’s scores in comparison to the estimated scores of the normative population.

The HiPIC relies on the FFM design and is constructed to capture all personality aspects in an individual through its five factors. The five factor scales and the corresponding facets are as follows: Benevolence (Egocentrism, Irritability, Compliance, Dominance, Altruism), Conscientiousness (Achievement-Striving, Order, Concentration, Perseverance), Extraversion (Shyness, Expressiveness, Optimism, Energy), Imagination (Creativity, Curiosity, Intellect), and Emotional Stability (Anxiety, Self-confidence). The terminology used for the five factors slightly differ from the original five-factor model proposed by Costa and McCrae (1992) to account for the shift from an adult target population to a youth target population. Benevolence is a broader version of the FFM factor *Agreeableness* as it also takes into consideration the child’s temperament and manageability from the parent’s perspective. Similarly, the Imagination factor represents the *Openness to Experience* factor from the FFM, but is unique in that it also comprises “intellect” items derived from adjective-based lexical studies (De Clercq et al., 2004). Lastly, Emotional Stability serves as a converse of *Neuroticism* and is interpreted as such.

The HiPIC has demonstrated a robust factor structure and high internal consistency across various studies, including samples from the psychopathic and social anxiety population among others (De Clercq & De Fruyt, 2012; Decuyper et al., 2012; Hampson et al., 2015; Miers et al., 2012). In the present study, the 18 personality facets generated from the collected HiPIC data were used to identify latent personality subgroups within the sample. Cronbach's alpha values for these facets ranged from .729 (Concentration) to .904 (Altruism).

Child Anxiety Impact Scale (CAIS). The CAIS is a measure for anxiety-related functional impairment across the school, family, and social settings (Langley et al., 2014). Although this measure contains a parent version and child version, only the parent version was employed in the treatment study. The measure was collected at both assessment time points (intake and post-treatment) and served as an outcome measure that was sensitive to treatment in the primary outcome paper (Adapted CBT > Standard-of-Practice CBT; Wood et al., under review). The CAIS contains 27 items that span across three domains: (a) impairment in the academic environment (CAIS-School), (b) impairment in the social environment (CAIS-Social), and (c) impairment in the home/family environment (CAIS-Family). Each item response is scored along a 4-point Likert scale, ranging from 0 ("not at all") to 3 ("very much"). A CAIS Total Score can then be generated by summing all 27 items, which can range from a minimum of 0 to a maximum of 108. This measure has demonstrated good internal consistency as well as strong convergent validity through significant correlations across various anxiety measures, such as the Multidimensional Anxiety Scale for Children (MASC) and Screen for Child Anxiety Related Emotional Disorders (SCARED) total scores (Langley et al., 2014). Both the total CAIS score and the CAIS subscale scores (school, social, and family) were used for the analyses. Cronbach's alpha values for the CAIS and its subscales are as follows: CAIS: .852; CAIS School: .796; CAIS Social: .793; CAIS Family: .654).

Pediatric Anxiety Rating Scale (PARS). The PARS is a clinician-rated measure used to assess the participants' anxiety symptom presence and severity (RUPP, 2002). In the RCT, it served as the primary outcome measure, exhibited sensitivity to treatment group (Adapted CBT exhibited more improvement than Standard-of-Practice CBT), and was only given to the parents (Wood et al., under review). In this measure, parents respond to clinician-prompted queries pertaining to their child and the presence (or absence) of 50 anxiety symptoms across six domains: (a) social interactions, (b) separation, (c) generalized, (d) specific phobia, (e) physical signs and symptoms, and (f) other. Once the anxiety symptoms are identified, symptom severity level is gauged along seven dimensions: (a) number of symptoms, (b) frequency (none to several hours per day), (c) severity of distress associated with anxiety symptoms, (d) severity of physical symptoms, (e) avoidance, (f) interference at home, and (g) interference out of home. Each of these dimensions are scored on a 5-point scale (0 for none, 1-5 for minimal to extreme). A total score is then generated by summing five of the seven dimensions (“number of symptoms” and “severity of physical symptoms” are excluded). The PARS has proven to be an instrument with strong psychometric properties (RUPP, 2002), including among the ASD population (Storch et al., 2012). Interrater reliability was acceptable and is reported elsewhere (see Wood et al., under review).

Data Analyses

Latent profile analysis. The first research aim was to identify possible personality subgroups within school-aged children in the ASD population. To do so, a latent profile analysis was conducted on the HiPIC data using the latent variable modeling software Mplus 8 (Muthén & Muthén, 2017). A combination of statistical and theoretical considerations drawn from the literature was used to determine the best fitting model (Masyn, 2013). For example, latent classes with less than 5% of the sample are typically considered spurious and were omitted from further consideration. The present study utilized both absolute fit indices (differences in observed and model-predicted means, correlations, and covariances) and relative fit indices. Absolute fit indices were used to compare the model's representation of the data to the actual observed data as a test of model consistency, while relative fit indices were used to compare two competing models' fit. Analysis included both inferential (e.g., likelihood ratio tests) and information-heuristic (e.g., information criterion values) relative fit comparisons for the sake of thoroughness. The absolute and relative fit indices were considered together to determine an optimal balance of model fit and parsimony (Masyn, 2013).

Among the relative fit indices common in the LPA literature, the Bayesian information criterion (BIC; Schwarz, 1978), sample-size adjusted BIC (SBIC; Sclove, 1987), and the bootstrapped likelihood ratio test (BLRT; McLachlan & Peel, 2000) were selected based on their status as the most reliable indicators of true model fit (Chen et al., 2017; Tein et al., 2013). As an inferential fit comparison, the BLRT compares the estimated model (with k classes) to a model with one less class (k - 1 classes), in which the p value obtained is an approximated probability that the given data have been generated by the "k - 1 class" model—a lower p value indicates the rejection of this model ("k - 1 class" model) in favor of the estimated model.

The BIC and SBIC are both information-heuristic fit comparisons, which allows a descriptive comparison across a set of models. The BIC is a model fit estimator founded on information theory which balances model fit and model complexity (i.e., a penalized-likelihood criterion). It describes the relative fit of a model by offering an estimate of the relative information lost when the given model is used to represent the process which generated the data. It is important to note that the criterion infers a Bayesian setup and penalizes model complexity more heavily than most other fit indices. As a result, BIC underestimates the number of classes in the best model fit when sample sizes are small. The SBIC takes this issue into consideration and adjusts for sample size by using a more forgiving penalty.

In addition to the BLRT, BIC, and SBIC, two descriptive quantifications of relative fit were used to further provide information regarding the best fitting model (Masyn, 2013). The Bayes Factor (BF) was calculated between candidate models to determine the ratio of the probability of Model A versus Model B being the correct model, while the approximate correct model probability (cmP) determined the probability a model was correct within a set of multiple models. A BF value between 1 and 3 is considered weak evidence for Model A, while a value between 3 and 20 is considered positive evidence, a value between 20 and 150 is strong evidence, and any value above 150 is considered very strong evidence (Raftery, 1995).

Once a best fitting model was selected, each latent class's membership size (and proportion of sample it accounted for) was reported. Each personality subgroup's HiPIC ranking for all 18 facets across the five personality factors (Benevolence, Conscientiousness, Extraversion, Imagination, Emotional Stability) were reported as well. Using a simple classification system based on the normal distribution curve, the decile scores were translated into qualitative categories to reflect their comparison to the typical-developing youth population for descriptive purposes: a decile score of 1-2 was labeled "very low", 2.001-3.2 as "low", 3.201-7.799 as "normative", 7.8-8.999 as "high", and 9-10 as "very high".

Analysis of covariance (ANCOVA) model. Revisiting the second research aim, the present study attempted to evaluate potential differences in treatment outcomes between the identified personality subgroups. Following Wood and colleagues' (under review) analytical design, a two-way factorial ANCOVA model was employed to compare treatment outcomes between the personality subgroups that emerged from the latent profile analysis. Treatment outcomes are represented by the change in CAIS total, CAIS subscales, and PARS scores over the course of the treatment study. Multiple ANCOVAs were conducted, in which each outcome measure was modeled independently. Participants' treatment condition (i.e., Adapted CBT, Standard-of-Practice CBT) and personality subgroup served as independent variables, while the pre-treatment measure score served as the covariate. An interaction term between treatment condition and personality subgroup was included to capture possible interaction effects. As such, significance testing determined whether personality subgroups differed on their response to CBT treatment for anxiety, as indicated by five outcome measures (CAIS, CAIS-School, CAIS-Family, CAIS-Social, and PARS).

For all ANCOVA models that revealed a statistically significant personality subgroup main effect or interaction effect, specific contrasts were conducted to further probe the nature of the findings. These specific contrasts were guided by visual inspection of the outcome measures' estimated marginal means, including each treatment condition-by-personality subgroup cell (e.g., the model-estimated CAIS score for Personality Subgroup 1, Adapted CBT condition). More specifically, these contrasts consisted of one type of main effect contrast (comparing outcome measures between personality subgroups regardless of treatment condition) and two types of simple contrasts (comparing outcome measures between personality subgroups within each treatment condition; comparing outcome measures between treatment conditions within each personality subgroup). This methodical approach focused on whether certain personality subgroup(s) demonstrated better treatment outcomes when compared to other subgroups, and whether this difference was contingent on the treatment condition.

Exploratory Analyses

Specific contrasts for non-significant findings. Although not all outcome measures and the accompanying omnibus ANCOVA models revealed a statistically significant personality subgroup effect or interaction effect, the relationship between personality attributes and treatment response in ASD research is largely unexplored and warrants further analysis. In addition, it is important to keep in mind the small sample sizes of some cells and the possibility that relevant findings are masked behind scarcely populated treatment condition-by-personality subgroup cells. Taking this into consideration, specific contrasts were conducted for non-significant ANCOVA models in order to further understand the data. This step in the analyses mirrors the specific contrasts in the main analyses, in which one type of main effect contrast and two types of simple contrasts were conducted.

Regression analyses of personality facets. The empirical nature of the FFM suggests that its attributes may be directly correlated to behavior and thoughts associated with both ASD and anxiety. As an example, it is likely that the anxiety and self-confidence facets in the Emotional Stability factor may be linked to both the neuroticism-related symptoms found in ASD and various clinical anxiety disorders. Given that certain personality facets may be more pertinent to a participant's response to a CBT treatment for anxiety, the facets should also be analyzed individually, not just as part of a subgroup pattern. To do so, the present study conducted individual regression analyses for each personality facet. Each regression equation included the pre- and post-treatment outcome measure scores along with a single personality facet. A single-block approach was used, in which the pre-treatment score and an individual personality facet was modeled together. This was done for each of the five outcome measures and was repeated three times – once for participants in the Standard-of-Practice CBT treatment condition only, once for participants in the Adapted CBT treatment condition only, and once for participants in either treatment condition (the combined analysis). A significant *p*-value indicated that the personality facet was a predictor of the outcome measure.

Results

Descriptive statistics for the HiPIC scores across the three treatment groups, as well as the overall sample, are provided in Table 2. Note that descriptive statistics for the CAIS and PARS at pre- and post-treatment are provided in Wood and colleagues (under review); specific descriptive statistics for these measures in relation to personality subgroups are presented below (see Table 5).

Main Findings

Latent Profile Analysis. A latent profile analysis of the participants' HiPIC facet decile scores is presented in Table 3. Each model was processed with 200 initial stage random starts and 50 final stage optimizations to ensure that a global maxima log likelihood value was obtained and replicated. Models that constituted a personality subgroup of less than 5% of the entire sample were deemed spurious and excluded from consideration.

Model selection. Results indicate that a five-class solution best fit the data with significant reductions in the BIC and SBIC through five classes. In comparison, the six-class solution demonstrated a moderate increase in the BIC and a marginal decrease in the SBIC. Similarly, the BLRT was significant ($p < 0.001$) up to the five-class solution, but the test was non-significant for the six-class solution ($p = 0.208$). A Bayes Factor comparison between the five- and six-class solutions provided strong evidence that the five-class solution presented superior fit (BF value > 150). Finally, when considering all six models, the cmP value of the five-class solution paralleled the findings (cmP = 1), indicating it as the best fitting model. The absolute fit indices reveal a strong fit between the model-predicted data and observed data, further supporting the aforementioned results. The difference between the observed means, correlations, and covariances from their model-predicted counterparts are 0.236, 0.393, and 1.250, respectively.

***Class (personality subgroup) characteristics*.** Figure 1 provides a graphical representation of the HiPIC profiles of the five subgroups (hereby referred to as "Groups 1-5"), and Table 4 summarizes the subgroups' prevalence and personality profiles identified in the LPA using the qualitative descriptors for ease of interpretation. Figure 1 is presented in a manner that best emphasizes the similarities and differences between the personality subgroups; the two connecting lines highlight Groups 2 and 3, representing the two largest subgroups which have considerably divergent treatment outcomes. Groups 2 and 3 each represented over a third of the sample, while Groups 4 and 5 both represented less than 10% of the sample individually. A preliminary inspection of the personality rankings highlighted the five personality subgroups' uniqueness. There were no instances in which all five personality subgroups shared the same ranking for a particular facet. Generally speaking, Group 5 ranked normative in both Conscientiousness and Emotional Stability facets, whereas Groups 1 through 4 all ranked low or very low (high/very high for reverse-scored facets). Additionally, Group 4 was the only personality subgroup that ranked normative in Extraversion – the other four subgroups ranked very low. Substantially, the personality subgroups were characterized as the following: Group 1 – low across the five factors except normative in Benevolence; Group 2 – low across the five factors except normative in Imagination; Group 3 – low across all five factors; Group 4 – low across Benevolence, Conscientiousness, and Emotional Stability, while normative in Extraversion and Imagination; Group 5 – normative across the five factors except very low in Extraversion. Analyzing the personality profiles on a more acute level, Group 2 ranked low in Achievement-Striving versus normative in Groups 1, 3, 4, and 5. Similarly, Group 4 was uniquely different from the other four groups in three facets (Optimism, Shyness, Creativity), while Group 5 was uniquely different than the other groups in two facets (Concentration, Perseverance). The distinctions between the five subgroups' personality profiles strengthen the case for the five-class solution as the best fitting model.

Two-Way Factorial ANCOVA Models. A two-way factorial ANCOVA was conducted for the five outcome measures each (see Table 6). Of the 202 participants that were assigned a personality subgroup, cases that were excluded from an intervention (e.g., did not meet inclusion criteria; $n = 41$) or assigned to a "treatment-as-usual" condition ($n = 17$) were excluded from the models. In addition, cases that were missing the pre- or post-treatment outcome measure data were excluded from that particular portion of the analyses.

Omnibus ANCOVAs. Across all five models and after controlling for pre-treatment measure scores, the personality subgroup main effect was only significant for the CAIS Total Score, $F(4, 101) = 2.774$, $p = .031$, while the interaction between personality subgroup and treatment condition was significant for both the CAIS Total Score, $F(4, 101) = 3.011$, $p = .022$, CAIS-School, $F(4, 102) = 3.077$, $p = .019$, and CAIS-Social, $F(4, 105) = 2.471$, $p = .049$. Results for ANCOVAs with CAIS-Family and PARS scores were all non-significant.

Specific contrasts. Guided by visual inspection of the means, specific contrasts conducted within the CAIS Total Score ANCOVA revealed several significant findings. When not considering treatment condition, Group 2 had a significantly worse (i.e., higher) score on the CAIS Total Score than Group 1, $p = .020$, 95% CI [1.05, 11.81], and Group 3, $p = .003$, 95% CI [2.17, 10.29]. Within the Standard-of-Practice CBT treatment condition, Group 2 scored significantly worse compared to Group 1, $p = .001$, 95% CI [5.81, 21.79], Group 3, $p = .007$ 95% CI [2.29, 14.32], and Group 4, $p = .046$ 95% CI [0.19, 22.69], independently. However, within the Adapted CBT treatment condition, no personality subgroups were statistically different on their CAIS Total Scores. Finally, when analyzing within personality subgroups, those in the

Group 2 Adapted CBT condition and Group 5 Adapted CBT condition scored significantly better (i.e., lower) on CAIS Total Scores compared to those in the Group 2 Standard-of-Practice CBT and Group 5 Standard-of-Practice CBT condition, $p = .014$ 95% CI [-13.36, -1.52] and $p = .049$ 95% CI [-22.98, -.032], respectively.

Specific contrasts conducted within the CAIS-School ANCOVA revealed similar discoveries. In the main effects contrasts (i.e., regardless of treatment condition), Group 2 scored significantly worse than Group 3 in the CAIS-School subscale, $p = .005$, 95% CI [1.05, 5.76]. In the simple contrasts within the Standard-of-Practice CBT treatment condition, Group 2 scored significantly worse than Group 1, $p = .004$, 95% CI [2.07, 10.91], Group 3, $p = .023$, 95% CI [0.58, 7.52], and Group 4, $p = .030$, 95% CI [0.69, 13.31]. In the simple contrasts within the Adapted CBT treatment condition, Group 1 scored significantly worse than Group 3, $p = .047$, 95% CI [0.05, 8.57] and Group 5, $p = .043$ 95% CI [0.17, 9.80]. Simple contrasts within each personality subgroup identified that the Group 1 Standard-of-Practice CBT condition outperformed (i.e., scored lower) than the Group 1 Adapted CBT condition, $p = .037$ 95% CI [-10.36, -0.32].

Simple contrasts for the CAIS-Social scale demonstrated that Group 2 performed significantly worse (i.e., higher score) than Group 1, $p = .006$, 95% CI [1.53, 9.16], Group 3, $p = .041$, 95% CI [0.13, 6.02], and Group 4, $p = .040$, 95% CI [0.26, 10.32], in the Standard-of-Practice CBT treatment condition. In addition, within Group 2 only, those in the Adapted CBT treatment condition outperformed those in the Standard-of-Practice CBT treatment condition on the CAIS-Social measure, $p = .005$, 95% CI [-7.08, -1.27].

Exploratory Findings

Specific Contrasts for Non-Significant Findings. Specific contrasts within the non-significant omnibus ANCOVAs (CAIS-Family, PARS) revealed a considerable number of findings. A main effects contrast for the CAIS-Family scale showed a significantly higher score in Group 2 when compared to Group 1, $p = .050$, 95% CI [0.001, 2.93], and Group 3, $p = .014$, 95% CI [0.30, 2.59], when not considering treatment condition. Within the Standard-of-Practice CBT condition, Group 2 remained significantly worse than Group 1, $p = .026$, 95% CI [0.29, 4.58], but not when compared to Group 3. Conversely, within the Adapted CBT condition, Group 2 was significantly worse than Group 3, $p = .032$, 95% CI [0.16, 3.43], but not Group 1.

Specific contrasts for the PARS within the Standard-of-Practice CBT treatment condition identified no statistical differences between the five groups. However, within the Adapted CBT treatment condition, simple contrasts identified Group 1 having performed significantly worse than Group 3, $p = .004$, 95% CI [1.47, 7.59], and Group 5, $p = .002$, 95% CI [2.03, 8.76]. Within Group 5, those in the Adapted CBT condition responded significantly better than the Standard-of-Practice CBT condition, $p = .044$, 95% CI [-9.95, -.14].

Regression Analyses. In the linear regression analyses, pre-treatment scores were statistically significant across all models. Analyses identified five personality facets as potential predictors for response to CBT treatment. The personality facet "Dominance" was statistically significant for CAIS-Family ($\beta = .259$, $t(60) = 2.396$, $p = .020$) in the Adapted CBT treatment condition, and was significant for CAIS Total Score ($\beta = .201$, $t(109) = 2.422$, $p = .017$), CAIS-School ($\beta = .189$, $t(110) = 2.126$, $p = .036$), and CAIS-Family ($\beta = .206$, $t(113) = 2.621$, $p = .010$) in the combined analysis (not differentiating between treatment groups). In summary, personality high in dominance is associated with worse treatment outcomes.

Higher "Achievement-Striving" is linked to statistically higher (i.e., worse) scores for CAIS Total Score (β = .276, $t(47) = 2.127$, $p = .039$) and CAIS-School (β = .298, $t(48) = 2.176$, $p = .035$) in the Standard-of-Practice CBT condition, but not in the Adapted CBT condition or combined analysis. Higher "Order" resulted in lower PARS outcomes in the Adapted CBT condition (β = -.243, $t(62) = -2.178$, $p = .033$) and in the combined analysis (β = -.284, $t(117) = -2.030$, $p = .045$), but not for the Standard-of-Practice CBT condition. Higher "Curiosity" is associated with higher scores in CAIS Total Score (β = .334, $t(47) = 2.593$, $p = .013$) in the Standard-of-Practice CBT condition and higher CAIS-Family score (β = .201 , $t(113) = 2.335$, $p = .021$) in the combined group analysis. Finally, higher "Intellect" is associated with lower CAIS-School scores in the Adapted CBT condition (β = -.237, $t(59) = -2.077$, $p = .042$).

Personality Profile Patterns. Investigation of Table 4 reveals personality profile patterns that substantiates the present study's main findings. Across the 18 personality facets, personality subgroups 2 and 4 often shared similar (and at times, the same) decile rankings, which consistently differed from Groups 1 and 3 (see Figure 1). This pattern occurred in the following facets: Compliance, Dominance, Irritability, Energy, Expressiveness, Curiosity, and Intellect. Among these seven facets, Group 5 resided within the two factions at a comparable frequency– four times with Groups 1 and 3 (Compliance, Irritability, Dominance, Energy) and three times with Groups 2 and 4 (Intellect, Curiosity, Expressiveness). The biggest rank disparity within a facet is Dominance, in which Groups 1, 3, and 5 ranked low/very low, while Groups 2 and 4 ranked high. The disparity between Groups 2 and 4 versus Groups 1 and 3 reflect the general treatment response pattern found throughout the outcome measures for the "overall" condition; that is, Groups 2 and 4 consistently had the worst scores across all five measures, while Groups 1 and 3 had the best scores and Group 5 was middling.

Discussion

Previous research has shown that high scores on autism measures, such as the Autism-Spectrum Quotient (AQ; Baron-Cohen et al., 2001) and Autism Diagnostic Observation Schedule – Generic (ADOS-G; Lord et al., 2000), are correlated with high neuroticism and low agreeableness, extraversion, and conscientiousness, and openness to experience (Lodi-Smith et al., 2018; Vuijk et al., 2018). The current study parallels these findings, as the sample of youth with ASD presented averages that match this profile. Within the identified personality subgroups, the two most populated subgroups, Groups 2 and 3, made up over 75% of the sample and reflected this analogue model presented by the literature. However, as pointed out in the study by Schriber and colleagues (2014), personality traits do not serve as perfect predictors of ASD versus typical-developing (TD) group membership. The less prevalent personality subgroups in the sample (Groups 1, 4, and 5) emphasize this point – there indeed exists smaller groups within the ASD population that deviate from this standard personality profile. This nuance could potentially explain the disparities in the literature as to why some personality factors consistently show a correlation with autism measure scores while some do not.

Similar distinctions found between personality subgroups in the present study can be found in the study by Schwartzman and colleagues (2015). Their study identified four FFM personality subgroups in an adult sample via cluster analysis, in which three subgroups had above-average neuroticism and none had below-average neuroticism. The same pattern has been replicated in the present study, in which four of the five subgroups ranked below-average in emotional stability and one ranked normatively. Interestingly, the present study's Group 2, which responded the worst to CBT treatment, had a near-identical personality profile with the Schwartzman study's Cluster 2, which demonstrated the highest autism score according to the RAADS-R measure (Ritvo Autism Asperger's Diagnostic Scale Revised; Ritvo et al., 2011). However, their study's statistical approach and large subsample size within each cluster makes it difficult to directly compare the four clusters from the current study's five identified personality subgroups. Even so, the Schwartzman study and the present study both provide evidence for clinically meaningful personality subgroups in the ASD population, which seem to parallel findings from the genetic literature in the ASD field (Hu et al., 2011; Veatch et al., 2014).

Not only are the subgroups distinct in their personality attributes, they also vary in their response to CBT treatment for anxiety. When taking all outcome measures into consideration, it seems that Group 2 responded poorly to CBT, while Group 4 responded moderately and Groups 5, 1, and 3 responded very well to the treatment (in order of worst-to-best treatment response: 2, 4, 5, 1, 3). More specifically, certain subgroups responded better to one treatment versus the other. This is most evident in Group 2, in which those in the Adapted CBT treatment condition considerably outperformed those in the Standard-of-Practice CBT treatment condition. On the other hand, those in Group 1 responded much better to Standard-of-Practice CBT than to Adapted CBT.

The same treatment response pattern (i.e., Groups 2 and 4 fared the worst, Groups 1 and 3 fared the best) that arose from the analyses can also be found in many of the personality facets. In seven of the 18 facets, it is evident that Groups 2 and 4 are strikingly similar and together they run counter to Groups 1 and 3, which too are analogous with one another. An additional three facets share a comparable sentiment, but has Groups 1 and 5 put together instead. The three potential predictors that emerged from the regression analyses fall within these two patterns, further implicating the possibility that certain personality facets (or combinations of facets) may serve as the driving force behind the subgroups' differing response to CBT treatment. In addition, the six facets (Optimism, Shyness, Creativity, Concentration, Perseverance, Achievement-Striving) that have one personality subgroup contrasted with the other four may all have an essential role in both defining its respective subgroup as well as modulating the effectiveness of certain treatments on participants.

It is difficult to decipher how or why certain personality subgroups responded better to CBT treatment. Group 5 had the highest Emotional Stability decile score and this was reflected in both the PARS and CAIS scores (i.e., Group 5 had the lowest score in both measures between all the subgroups). Despite this, the subgroup neither responded best or worst to the CBT treatment, but rather ranked middling. It suffices to say that response to CBT treatment for anxiety is not simply dependent on one's pre-treatment anxiety severity level.

Based on the current findings, it seems that the personality profiles themselves dictate an individual's response to treatment. Due to the complexities that underlie the relationships between the personality facets, it is necessary to explore the identified subgroups' personality profiles as a whole when considering how it may impact their treatment response. The results suggest that multiple facets contribute to the groups' treatment response rank order (worst-to-best: 2, 4, 5, 1, 3). Particularly, it seems that those who responded best to the treatment demonstrated a willingness to cooperate (e.g., normative compliance, low dominance), reservation in social behavior (e.g., low energy and expressiveness), and interestingly, an impartialness towards novelty and knowledge (e.g., low curiosity and intellect). Conversely, it seems that those who benefit the most from the CBT treatment for anxiety are the individuals who won't contend with the therapist, challenge the learning material, and diverge from the focus of the sessions.

Beyond the personality profiles, a few facets may perhaps serve as the driving force behind the treatment response pattern. Dominance seems to play a significant role – the facet (found in the Benevolence factor) presents a strong negative correlation with treatment response, in which those who showed high or very high scores responded poorly. This makes sense in the context of clinical treatment, as those with a dominant nature will prefer social topics of their own interest, leading to a harder time learning from the therapist and difficulty absorbing concepts from the lesson. Similarly, low scores on the Curiosity facet (under the Imagination factor) led to better treatment response. This could possibly be explained by the notion that those with lower curiosity are less prone to diverge from the lesson concepts and can readily incorporate the cognitive training that is essential in CBT treatments.

Further probing into the relationship between personality profiles and treatment response, it is important to explore why the study's two CBT treatments for anxiety had differential impact depending on personality subgroups. Standard-of-Practice CBT was clearly the more effective treatment for those in Group 1, but the Adapted CBT was substantially better than Standard-of-Practice CBT for those in Group 2. This disparity can perhaps be attributed to differences between the two subgroups' personality profiles. The simplest explanation may be that Standard-of-Practice CBT is most effective when used with individuals who demonstrate below average scores in Imagination or non-below average facet scores in Extraversion. The structure of the Standard-of-Practice CBT treatment is very methodological, and perhaps this induces a feeling of repetitiveness and boredom in the participants. Those with low scores in Imagination, however, may be less likely to be distracted and stray away from the step-by-step approach of

Standard-of-Practice CBT. The treatment also requires consistent, meaningful communication with the therapist and the willingness to share one's thoughts. Higher scores in Extraversion could possibly generate more frequent and higher quality learning opportunities within the treatment. This explains why Groups 1 and 3, which both scored low/very low on Curiosity and Intellect, were two of three subgroups that made moderate gains from Standard-of-Practice CBT while Groups 2 and 5 did not. Even though Group 4 ranked normative in Imagination, it was the only subgroup that ranked normative in Extraversion, which could explain why it still made substantial improvements through Standard-of-Practice CBT.

On the other hand, the Adapted CBT treatment is presented in a personalized, modular format with various stimuli. Although the treatment sessions are longer than the ones in Standard-of-Practice CBT, the usage of time is very different. In particular, 45 minutes of the session is dedicated to working with the parents alone or together with the whole family. The interactive approach of the Adapted CBT treatment as well as its parent components may be compensating for individuals who demonstrate non-below average Imagination scores or below average Extraversion scores. From the study's findings, it can be postulated that these differences in the CBT treatments' active ingredients may be a primary reason why the Adapted CBT condition is more effective when working with children that may not respond well to Standard-of-Practice CBT. However, no other study has evaluated response to CBT treatment for anxiety within the context of personality facets and the ASD population; and so, the present study's exploratory findings and its interpretation are unsubstantiated and has yet to be fully deciphered. Further research is required to better understand individual personality facets, their interactions, and the profiles they form in context of CBT treatment response for the ASD youth population.

Given the scope of the current study and its small sample size, it is presumptuous to make any definitive claims as to whether the different personality profiles reflect multiple subtypes of autism or which personality facets serve as key predictors in treatment response. As such, the relationship behind the latent construct of personality and the symptom profiles and etiologies of autism remain unclear. However, the study did succeed in identifying personality subgroups within the ASD population and concluded that particular subgroups responded better to CBT treatment for anxiety while other subgroups responded worse. Accordingly, this serves as very strong evidence for the use of LPA to identify meaningful, homogeneous subgroups in the ASD population.

Limitations

Although the present study was successful in identifying meaningful personality subgroups and differences in treatment outcomes within the ASD population, several methodological limitations must be acknowledged. As the first study of its kind, there is very little evidence from the literature that can be used to support or compare with the present findings, or even serve as a precedent for the analytical approach. Although it is an empirically sophisticated method, latent profile analysis is seldom used within the ASD youth population and has never been used within the context of personality facets and ASD. The identified personality subgroups' reliability across multiple samples remains to be seen in the autism research field.

This concern is exacerbated by the study's small sample size. Although 202 cases serve as a moderately sufficient number in a randomized, controlled CBT treatment trial in ASD research, the analysis of five personality subgroups across two treatment conditions facilitated the sample into small cell sizes (i.e., small representation of certain personality group-by-treatment condition combinations). As a result, it is entirely possible that some of the analyses lacked the statistical power to identify significant patterns. In addition, the study only included verbal children with IQs above 70 and does not fully represent the entire ASD population. Given the limited representation and small sample size, there may be certain personality subgroups in the ASD youth population that were not represented by the study's sample.

Another limitation of this study was its ability to interpret personality facets and profiles as potential predictors in CBT treatment response. Although assertions were made by finding patterns between differences in treatment response and personality attributes across personality subgroups, this approach relied heavily on identifying disparities between the subgroups' profiles. However, some facet scores presented a small value range across all five subgroups; because of this lack of contrast, it was difficult to determine exactly how those facets may affect an individual's response to treatment. For example, although no statistical difference was found between subgroups on the PARS score in the Standard-of-Practice CBT treatment condition, this could possibly be attributed to all five subgroups having relatively normative to high anxiety. Ultimately, the relationship between personality attributes (both facets and profiles) and response to CBT treatment for anxiety requires further research.

Conclusion

Current autism research has identified ASD as a heterogeneous disorder with multiple etiologies and varying levels of both symptom expression and severity between individuals. The present study has identified meaningful, homogeneous subgroups that demonstrate key discernable personality attributes, and these profiles appear to be potential predictors of response to CBT treatment for anxiety in individuals with ASD. The discovery of personality subgroups within the ASD population may be one step closer to disentangling the heterogeneous nature of ASD and perhaps could inform the identification of possible subtypes within the broader autism clinical diagnosis, paralleling the framework established in the “multiple autisms” theory. Additionally, the present study suggests that optimal treatment interventions may be elucidated based on differences in individuals’ personality profiles. In the future, personality screening may possibly be used to design and personalize treatment plans unique to each individual.

The present findings will not only contribute to advancements in the clinical setting, but will also translate to applied settings such as the school and home environment. Successful implementation of personalized treatment for children with ASD is critical to successful inclusion in the school setting (Smith & Iadarola, 2015). The identification of meaningful personality subgroups and efficacious personalized treatments may lead to a reduction of maladaptive autism and comorbid symptoms, thus maximizing the academic and social learning opportunities available to school-aged youth.

Future research should aim to replicate the present study’s methodology and findings. By taking a latent profile analysis approach to other samples of youth with ASD, a better understanding of the personality subgroups within the ASD population can be garnered and their differences in treatment response can be further validated. Accordingly, future research should determine if differences in treatment response found between the present study’s identified personality subgroups may translate to other treatments for autism (e.g., applied behavioral analysis) or anxiety (e.g., mindfulness-based stress reduction), or perhaps even to medication (e.g., antipsychotics, antidepressants). It is also necessary to continue conducting research at the intersection between personality and autism to gain deeper insight into the relationship between personality facets and treatment response. Finally, the distinctions between personality subgroups should be corroborated along other levels of evidence, such as through genetic and neuroscience methods. The convergence of findings across multiple research domains may serve as the cornerstone in identifying homogeneous subgroups in the ASD population and in constructing optimal personalized interventions.

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Table 1

Sample Demographics, Medication Usage, and Pre-treatment Scores

	Study Sample* (*SD*) n = 202
Sex (male)	160 (79.2%)
Age	9.97 (1.78)
Ethnic background (%)	
Latino/a / Hispanic	30 (15.3%)
Black / African-American	13 (6.4%)
Asian	17 (8.4%)
Caucasian	129 (63.9%)
Native Hawaiian / Pacific Islander	1 (0.5%)
American Indian / Alaskan Native	3 (1.5%)
Multiracial	8 (4.0%)
WISC-IV Full Scale IQ	100.65 (15.97)
ADOS Score	12.58 (4.62)
Medication Use (%)	
Stimulant	21 (10.4%)
SSRI	18 (8.9%)
Atypical Antipsychotic	8 (4.0%)
Alpha Agonist	13 (6.4%)
Anti-convulsant	3 (1.5%)
SNRI	2 (1%)
Benzodiazepine	1 (0.5%)
Pre-Treatment Scores	
CAIS	29.61 (11.83)
CAIS-School	14.06 (6.09)
CAIS-Social	10.14 (6.34)
CAIS-Family	6.69 (3.67)
PARS	16.48 (3.07)

Note. ADOS = Autism Diagnostic Observation Schedule, CARS = Childhood Autism Rating Scale, SSRI = selective serotonin reuptake inhibitor, SNRI = serotonin-norepinephrine reuptake inhibitor, CAIS = Child Anxiety Impact Scale, PARS = Pediatric Anxiety Rating Scale.

*Of the 213 participants in the dataset, 11 cases were missing HiPIC data and excluded from the present study's analyses.

Table 2

Sample Personality Facet and Factor Decile Scores

		Treatment Condition Subsamples**		
	Study Sample* (*SD*)	Standard-of-Practice CBT (*SD*)	Adapted CBT (*SD*)	TAU (*SD*)
	n = 202	*n* = 70	*n* = 74	*n* = 17
Facet Decile Scores				
Altruism	2.69 (2.49)	2.39 (2.35)	2.64 (2.39)	3.53 (2.70)
Compliance	3.73 (2.83)	3.83 (2.90)	3.77 (2.94)	4.00 (2.94)
Dominance (R)	4.97 (3.61)	5.04 (3.72)	4.70 (3.53)	4.47 (3.54)
Egocentrism (R)	8.48 (2.28)	8.5 (2.45)	8.23 (2.36)	8.94 (1.56)
Irritability (R)	7.14 (3.11)	7.31 (3.12)	6.74 (3.32)	6.47 (3.02)
Achievement-Striving	3.93 (3.04)	3.91 (3.02)	3.65 (3.01)	5.18 (2.81)
Concentration	2.78 (2.11)	2.76 (2.04)	3.12 (2.23)	2.24 (2.05)
Order	3.03 (2.34)	3.11 (2.50)	3.05 (2.42)	2.94 (2.05)
Perseverance	2.78 (2.11)	2.36 (2.25)	2.82 (2.17)	2.41 (1.84)
Energy	3.03 (2.34)	3.03 (2.64)	3.30 (2.96)	4.35 (3.57)
Expressiveness	2.50 (2.13)	3.47 (2.88)	3.84 (2.94)	4.00 (3.48)
Optimism	3.30 (2.88)	1.66 (1.63)	1.38 (1.18)	1.82 (1.47)
Shyness (R)	3.74 (3.06)	9.03 (1.67)	9.20 (1.68)	8.59 (2.65)
Creativity	1.57 (1.49)	4.90 (3.13)	5.74 (3.19)	4.24 (3.38)
Curiosity	8.98 (1.96)	2.86 (2.65)	3.41 (2.83)	4.06 (2.95)
Intellect	3.03 (2.28)	3.13 (2.22)	3.15 (2.42)	2.53 (2.55)
Anxiety (R)	7.74 (2.59)	8.19 (2.35)	7.42 (2.78)	8.00 (1.84)
Self-Confidence	2.56 (2.10)	2.44 (2.12)	2.69 (2.08)	2.71 (2.47)
Factor Decile Scores				
Benevolence	3.10 (2.69)	2.91 (2.66)	3.35 (2.79)	3.47 (2.92)
Conscientiousness	2.62 (2.09)	2.63 (2.18)	2.70 (2.03)	2.82 (2.13)
Extraversion	1.87 (1.77)	1.84 (1.77)	1.61 (1.34)	2.29 (2.49)
Imagination	3.45 (2.65)	3.14 (2.47)	3.81 (2.87)	3.18 (2.38)
Emotional Stability	2.49 (2.04)	2.14 (1.95)	2.73 (2.07)	2.29 (1.86)

Note. (R) indicates the facet is reverse-scored for its respective Big Five factor.

*Of the 213 participants in the dataset, 11 cases were missing HiPIC data and excluded from the present study's analyses.

**The treatment condition subsamples fall under the "Study Sample" (*n* = 202) and only include cases that had both sufficient HiPIC data and an assigned treatment condition.

Table 3

Model Fit Indices for One- to Seven-class Solutions in the Latent Profile Analysis using HiPIC Facet Decile Scores

Model	BIC	SBIC	BLRT *p*-value
one-class	17203.595	17089.54	—
two-class	16869.636	16695.385	< .0001
three-class	16661.426	16426.979	< .0001
four-class	16551.263	16256.62	< .0001
five-class	**16502.919**	16148.081	**< .0001**
six-class	16560.877	16145.843	0.2083
seven-class	16594.571	16119.341	1.0000

Note. BIC = Bayesian Information Criterion, SBIC = Sample-sized adjusted Bayesian Information Criterion, BLRT = Bootstrapped Likelihood Ratio Test.

Table 4

Identified Subgroups' Membership Size, Proportion, and Personality Profiles

	Class 1	Class 2	Class 3	Class 4	Class 5
Membership Size (Proportion)	31 (15.3%)	69 (43.2%)	68 (33.7%)	14 (6.9%)	20 (9.9%)
Altruism	N	VL	VL	N	N
Compliance	N	VL	N	L	N
Dominance (R)	VL	H	L	H	L
Egocentrism (R)	N	VH	VH	VH	N
Irritability (R)	N	VH	N	H	N
Achievement-Striving	N	L	N	N	N
Concentration	L	L	L	L	N
Order	N	L	L	L	N
Perseverance	L	VL	VL	VL	N
Energy	L	N	L	N	L
Expressiveness	L	N	L	N	N
Optimism	VL	VL	VL	N	VL
Shyness (R)	VH	H	VH	N	H
Creativity	N	N	N	H	N
Curiosity	L	N	L	N	N
Intellect	VL	N	L	N	N
Anxiety (R)	N	H	H	H	N
Self-Confidence	VL	L	VL	N	N

Note. Rankings are according to a simple classification system based on the subgroups' raw decile scores, in comparison to a normative Flemish youth population. L = very low (1-2), L = low (2.001-3.2), N = normative (3.201-7.799), H = high (7.8-8.999), VH = very high (9-10). (R) indicates the facet is reverse-scored for its respective Big Five factor.

Table 5

Pre- and Post-Treatment Measure Scores for Identified Personality Subgroups

	Class 1		Class 2		Class 3		Class 4		Class 5	
Membership Size (Proportion)	31 (15.3%)		69 (43.2%)		68 (33.7%)		14 (6.9%)		20 (9.9%)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
CAIS										
Pre	30.60	9.96	30.34	11.90	31.23	11.53	30.92	14.49	19.55	9.28
Post	16.67	9.07	22.28	9.42	18.02	11.36	22.86	15.30	12.80	7.86
CAIS-School										
Pre	15.33	5.26	13.47	5.86	15.58	6.16	15.29	5.94	8.10	4.14
Post	8.67	6.65	10.26	4.36	8.38	5.82	10.50	8.07	4.87	4.27
CAIS-Social										
Pre	11.00	6.06	10.20	6.19	10.55	6.33	11.04	8.29	6.65	5.13
Post	5.63	3.87	7.21	5.29	6.51	5.93	8.89	7.20	4.93	4.14
CAIS-Family										
Pre	6.06	4.37	7.81	3.71	6.34	3.35	6.11	3.52	5.40	2.72
Post	3.53	2.93	5.53	3.03	3.52	2.83	5.33	4.24	3.33	2.23
PARS										
Pre	16.77	2.64	17.25	2.88	15.57	3.50	18.15	1.86	15.45	2.11
Post	11.90	4.42	11.51	3.16	10.04	4.75	13.70	4.19	8.47	3.98

Note. Cases that were missing the pre- or post-treatment outcome measure data were excluded from that particular portion of the analyses.

Table 6

ANCOVA Results for Response to Treatment by Personality Subgroups and Treatment Condition, Controlling for Pre-treatment Scores

Outcome Measure	Predictor Variables	*SS*	*df*	*MS*	*F*
CAIS (n = 112)	Personality Subgroup	867.92	4	216.98	2.774*
	Personality Subgroup *Treatment Condition (Interaction Term)	941.87	4	235.47	3.011*
CAIS-School (n = 113)	Personality Subgroup	222.14	4	55.54	2.176
	Personality Subgroup *Treatment Condition (Interaction Term)	314.06	4	78.52	3.077*
CAIS-Social (n = 116)	Personality Subgroup	72.38	4	18.10	0.907
	Personality Subgroup *Treatment Condition (Interaction Term)	197.25	4	49.31	2.471*
CAIS-Family (n = 116)	Personality Subgroup	50.31	4	12.58	1.984
	Personality Subgroup *Treatment Condition (Interaction Term)	27.91	4	6.98	1.101
PARS (n = 120)	Personality Subgroup	54.90	4	13.73	.962
	Personality Subgroup *Treatment Condition (Interaction Term)	131.53	4	32.88	2.304

Note. Response to treatment is assessed through five outcome measures. Cases from the TAU condition and cases missing pre-treatment or outcome measure data were excluded from analyses. CAIS = Child Anxiety Impact Scale, PARS = Pediatric Anxiety Rating Scale. *SS* = sum of squares, *df* = degrees of freedom, *MS* = mean square, *F* = *F*-ratio.

*p < .05

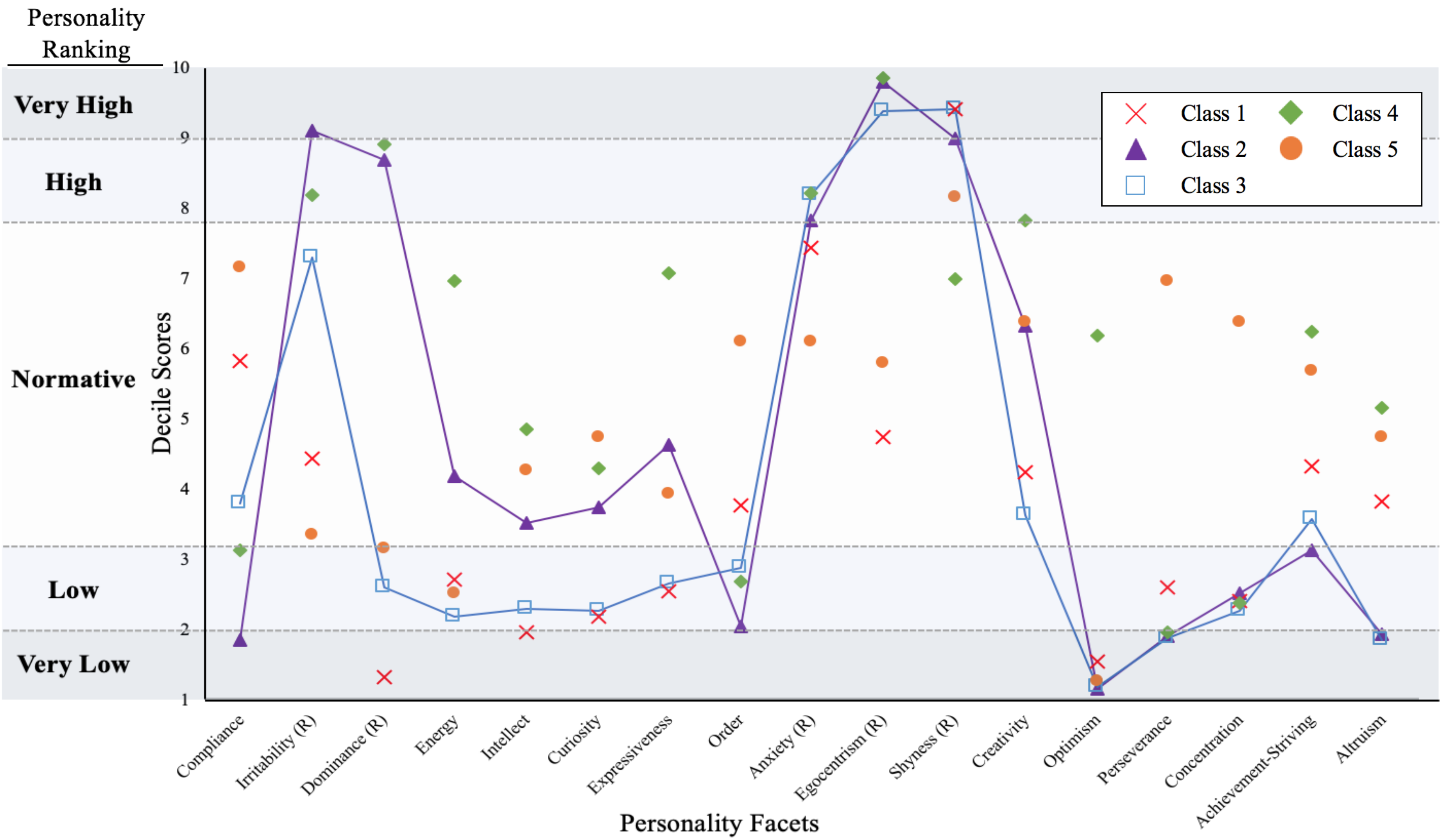

Figure 1. Identified personality subgroups' profile patterns. This figure illustrates the similarities and differences between personality subgroups across the 18 facets. Order of the facets are reorganized to underscore emergent patterns; the two connecting lines highlight Groups 2 and 3, representing the two largest subgroups which have considerably divergent treatment outcomes. Personality rankings are according to a simple classification system based on the subgroups' raw decile scores, in comparison to a normative Flemish youth population.