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# Evidence for Latent Classes of IQ In Young Children with Autism Spectrum Disorder

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## Abstract

Autism is currently viewed as a spectrum condition including strikingly different severity levels. IQ is consistently described as one of the primary aspects of the heterogeneity in autism. To investigate the possibility of more than one distinct subtype of autism based on IQ, both latent class analysis and taxometric methods were used to classify Mullen IQ scores in a sample of children with autism spectrum disorder (N=456). Evidence for multiple IQ-based subgroups was found using both methods. Groups differed in level of intellectual functioning and patterns of verbal versus nonverbal ability. Results support the notion of distinct subtypes of autism which differ in severity of intellectual ability, patterns of cognitive strengths and weaknesses, and severity of autism symptoms.

Autism is characterized by impairments in social interaction and communication, and by a restricted repertoire of activities and interests. Children and adults with autism have specific deficits in social and emotional information processing (Davies, Bishop, Manstead, & Tantam, 1994; Dawson, Meltzoff, Osterling, & Rinaldi, 1998), which are considered to be common features of individuals with the disorder. Yet autism is also characterized by wide variability in more specific impairments, range of symptoms, levels of adaptive and intellectual functioning, and prognosis. These differences in presentation make conceptualization of the disorder difficult, especially given that diagnosis is based on behavioral observations and standardized parental interviews administered by clinicians. Thus, in almost all cases, behavioral characteristics – rather than laboratory or medical tests –determine diagnostic assignment.

Because of the significant symptom heterogeneity found in autism, it is often conceptualized as ‘autism spectrum disorder’ (ASD). Variability in IQ is one of the most salient dimensions of this heterogeneity. Both DSM-IV (APA, 1994) and ICD-10 (WHO, 1992) definitions of

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Asperger syndrome include cognitive developmental level as one of the key features distinguishing it from autism. It is estimated that 70% of individuals with autism have IQs in the mentally retarded range (Fombonne, 2003), yet some individuals have above average intellectual ability (Miller & Ozonoff, 2000). Moreover, the IQ profiles of individuals with and without mental retardation tend to differ, with higher IQ individuals typically having a higher Verbal IQ on average (Ghaziuddin & Mountain-Kimchi, 2004; Gilchrist, Green, Cox, Burton, Rutter, & Couteur, 2001). However, there is extreme individual variability in IQ, making it unlikely that a specific cognitive profile can be used for differential diagnostic purposes (Filipek et al., 1999; Siegel, Minshew, & Goldstein, 1996). Nevertheless, researchers have used various strategies to subtype individuals with autism. Some have focused on medical conditions or known biological etiologies contributing to the disorder. Miles et al. (2005) defined subtypes of autism based on whether individuals had features that were stable from birth, suggesting an organic factor, including all of the syndromes that are currently acknowledged as causes of autism (e.g., Fragile X). These individuals, comprising what the authors call the ‘complex’ autism group, also tend to have more seizures, dysmorphic physical features, microcephaly, lower IQs, and a tendency toward poorer outcome than the ‘essential’ autism group. The ‘essential’ autism group is characterized by higher incidence of sibling recurrence and a family history of autism, higher male to female ratio, higher likelihood of regression and macrocephaly, and overall higher IQs. According to Miles et al., assigning individuals to the complex and essential groups allows for the first stage of characterizing the etiologic heterogeneity of those with ASDs. This separation might be especially useful for genetic analyses because it provides a more homogenous group of individuals (essentials). However, until the etiological substrates of autism are identified, it is impossible to know how truly homogenous this group is.

Additional research has focused on defining ASD subgroups according to behavioral patterns of social interaction. Wing and Gould (1979) first characterized autism according to three subtypes: aloof, passive, or active-but-odd. The aloof subtype, which includes children who tend to reject contact and avoid gaze, is typically the most impaired and severely autistic (e.g., Castelloe & Dawson, 1993; Sevin, Matson, Coe, Love, Matese, & Benavidez, 1995). Levels of IQ tend to correspond to social typology, with the aloof group having the lowest IQ, followed by the passive and then active-but-odd groups (Borden and Ollendick, 1994). The aloof group also tends to have the lowest levels of adaptive behavior, worse language and communication skills, and higher ratings of stereotyped behavior/restricted interests. Intellectual functioning likely accounts for a large proportion of the variance in predicting language and communication skills, the presence of stereotyped behaviors, and other prototypically autistic behaviors, which may partly contribute to group assignment. Indeed, Volkmar et al. (1998) found that IQ is often a predictor of social subtype assignment; however, it may not fully account for it.

Because level of intellectual functioning may be among the strongest indicators of subtype, investigators have often attempted to divide the ASD group by choosing an a priori IQ cutoff in order to designate and then characterize the resulting high- and low-functioning groups (Bartak and Rutter, 1976; Allen et al., 2001). The lower- functioning cognitive subgroup, defined as having an IQ below 70 or 80, tends to exhibit more self-injury, stereotypies, and prototypical autism behaviors. Yet such cutoff points are somewhat arbitrary, making it likely that there is diagnostic overlap between the cognitive subgroups generated. Furthermore, distinctions between verbal and nonverbal information processing abilities are often not explored, but may be important in identifying subtypes in autism. Tager-Flusberg and Joseph (2003) investigated discrepancies between verbal and nonverbal IQ in children with autism and found children with discrepantly high nonverbal skills relative to verbal skills had greater social impairment independent of absolute level of verbal ability and overall ability.

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Attempts have been made to investigate subgroups within a dimensional construct on the basis of non-unimodal distributions. Meehl (1995) notes that bimodality and marked skewness may be suggestive of latent groups, however, the presence of bimodality is neither a necessary nor sufficient condition for the existence of latent subgroups. For example, when two latent distributions have a mean difference of 2 SDs and equal variances, bimodality may not even be apparent. On the other had, Grayson (1987) has noted that even when bimodality is observed in measured variables the underlying structure may still be a continuous dimension.

Statistical strategies may provide a more empirical basis for characterizing individuals within possible ASD subgroups. A review of the literature indicates that most cluster analytic studies yield 2, 3, or 4 subgroups based on degree of impairment. Sevin et al. (1995), for example, used cluster analysis to classify 34 children with autism or PDD-NOS into 4 groups, described as ranging from high-functioning to low-functioning (severe) autism, with IQ decreasing with severity, and differing significantly between groups. Similarly, Eaves, Ho, and Eaves (1994) used a standard clustering algorithm and principal components analysis of variables to parse 166 children into 4 groups ranging from ‘typically autistic’ and lower-functioning to a higher-functioning group that more closely resembled Asperger syndrome. Again, severity of autism was related to intellectual impairment in that the most impaired subtype had the lowest average IQ. In a longitudinal examination of 138 school age children with autism, Stevens et al. (2000) employed hierarchical agglomerative cluster analysis to validate a 2 group solution, in which cognitive level was the largest separating variable. Children who were lower-functioning as defined by nonverbal IQ at pre-school tended to show poorer outcome at school age, suggesting that nonverbal IQ is an extremely potent predictor membership among school-age children.

Often, cluster analytic techniques have been used to determine which behavioral features of autism tend to correlate or account for the majority of variance – or which factors ‘cluster’ together. Once a cluster solution is determined and individuals are assigned to groups, the subtypes are characterized using various descriptors, including level of intellectual functioning. In using IQ as a descriptor only *after* the groups have been defined, however, these analyses make it difficult to determine the true role of intellectual capacity in the formation of subgroups, and the actual distribution of IQ in the samples. Few investigators have focused exclusively on cognitive functioning as the empirical indicator of subgroup classification. Those who have specifically investigated the role of intellectual capacity in differentiating ASD subtypes have often found that IQ is the most significant contributor in discriminating between groups and the basis of differences between subtypes (e.g., Miller and Ozonoff, 2000).

Although the goal of cluster analysis is to determine the categories underlying autism spectrum disorders, these methods often yield groups with considerable diagnostic overlap. Unfortunately, under such conditions, cluster analysis often (a) fails to identify the correct number of clusters in datasets where group membership is known, and (b) performs poorly in sorting individuals into subgroups (e.g., Krieger & Green, 1999; Tonidandel & Overall, 2004). Furthermore, it has long been recognized among statisticians that clustering algorithms partition datasets into subgroups, even if the distributions are known to be continuous (see Beauchaine, 2003). Thus, results derived solely from cluster analysis do not provide strong evidence for subgroups of autism, and do not eliminate the possibility of a spectrum of autistic-like disorders (Prior et al., 1998). In fact, data from eight cluster analytic studies suggest that children with PDD-NOS may fit into one of two overlapping groups, and that the subtypes resemble each other, existing along a continuum, and differing only by degree of impairment (Myhr, 1998). In a review of subtyping studies of autism, Beglinger and Smith (2001) posit their ‘best guess’ that symptom heterogeneity can be

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represented by three continua (developmental delay, social impairment, and repetitive behaviors) and rough divisions can be drawn along these continua yielding four subgroups. The authors also note the weaknesses associated with cluster analytic techniques, including the dependence on the investigators' choice of variables and characteristics of the sample. This conclusion of the presence of a "continuum containing subgroups" highlights the continued difficulty researchers in this area have in determining whether true differences between subgroups in autism can be reliably distinguished.

In part as a result of the limitations of cluster analysis, additional classification techniques, including latent class analysis (LCA) and taxometrics, have been developed. Although rarely used to evaluate whether subgroups of autism exist, these techniques offer several advantages over clustering algorithms (Beauchaine & Marsh, in press). For example, LCA provides objective measures of fit for comparing alternative subgroupings, and taxometric analyses are far less prone to identify spurious subgroups within continuous distributions. The lone example of taxometric analysis (based on an adaptation of the regression-mixture model, Golden & Mayer, 1995) in autism is the Autism and Language Disorders Nosology project (Rapin, 1996) which found evidence for 2 discrete subgroups, or taxa, in a sample of children with PDD (Fein, et al., 1999) with the nonverbal IQ of about 65 optimally dividing the groups. In the present paper, both LCA and maximum covariance (MAXCOV), the most widely studied taxometric algorithm, were used to address the question of whether subgroups of ASD can be identified from the verbal and nonverbal IQ scores of probands.

To summarize, although it is unclear whether distinct subtypes of autism exist, a recurring pattern emerges in which IQ strongly predicts social functioning, adaptive behavior, severity of symptoms, and prognosis (Coplan & Jawad, 2005; Howlin, Goode, Hutton, & Rutter, 2004; Bolte & Poustka, 2002; Liss et al., 2001; Carpentieri & Morgan, 1996). We used both MAXCOV and LCA to analyze verbal and nonverbal IQ scores obtained from a large sample of preschool-aged children diagnosed with ASD, who were evaluated through the NICHD Collaborative Program of Excellence in Autism (CPEA). Although cluster analysis offers no proven means of choosing among models with different numbers of classes and tends to over-extract classes when defining subtypes, LCA and MAXCOV offer an alternative and more conservative approach to determine whether there is a bimodal or multimodal distribution of intellectual functioning among individuals with autism. By using young children in this analysis, we hoped to minimize individual difference related to experience and treatment.

## Method

### Participants

Participants were 456 children (370 boys (81%), 86 girls (19%)) with autism spectrum disorder between the ages of 24 and 66 months (mean 43.4, SD 8.7) who were participating in studies affiliated with the NICHD Collaborative Program of Excellence in Autism (CPEA). Exclusionary criteria included the presence of a neurological disorder of known etiology, significant sensory or motor impairment, major physical abnormalities, and history of serious head injury and/or neurological disease. Diagnosis of ASD was based on administration of the Autism Diagnostic Observation Schedule-Generic and Autism Diagnostic Interview-Revised. All of the children met criteria for autism (N=357, 78%) or autism spectrum disorder (N= 99, 22%) on the ADOS-G. Nearly all of the children met criteria for a diagnosis of autism on the ADI-R (N=431, 95%) with the remaining 25 children within 2 pts of a diagnosis of autism on the ADI-R. Informed consent was appropriately obtained from each child's parent/guardian prior to their participation in this study.

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## Measures

**Autism Diagnostic Interview – Revised (ADI-R; Lord, Rutter, & Le Couteur, 1994)—**The ADI-R is a structured, standardized parent interview developed to assess the presence and severity of symptoms of autism in early childhood across all three main symptom areas: social relatedness, communication, and repetitive, restrictive behaviors. The ADI-R has been psychometrically validated across a wide range of ages and severity levels in autism. Each site contained one experimenter who was trained to reliability by Dr. Catherine Lord on the ADI-R; that person then trained other raters in her lab to a reliability of 85% or better.

**Autism Diagnostic Observation Schedule – Generic (ADOS-G; Lord et al., 2000)—**The ADOS-G is a semi-structured standardized interview using developmentally appropriate social and toy-based interactions in a 30–45 min interview to elicit symptoms of autism in four areas: social interaction, communication, play, and repetitive behaviors. The ADOS-G consists of four different modules, each directed at a particular level of language ability. In the present study, all participants received Module 1, for preverbal children or those just beginning to speak. The ADOS-G has been psychometrically validated across a wide range of ages and severity levels in autism (Lord et al., 2000). Dr. Lord trained an experimenter at each site to reliability on the ADOS-G at the University of Chicago; that person then trained other raters in the lab to a reliability of 85% or better.

**Mullen Scales of Early Learning (MSEL; (Mullen, 1989)—**The MSEL is a standardized developmental test for children ages 3 months to 60 months consisting of five subscales: gross motor, fine motor, visual reception, expressive language, and receptive language. The last four are combined to yield an overall composite score of intellectual functioning. The MSEL demonstrates strong concurrent validity with other well-known developmental tests of motor, language, and cognitive development. The MSEL was administered to all participants according to standard instructions by raters trained in assessing young children with autism and other developmental disorders. Reinforcers for all participants in all groups were used at times to reward cooperation and attention. A set of four developmental quotients for each participant was constructed dividing the age equivalence score for each Mullen subscale by the child's chronological age and then multiplying by 100 ((AE/CA) * 100). An overall verbal score was calculated by averaging the receptive and expressive language IQ scores, and a nonverbal IQ was calculated by averaging the visual reception and fine motor IQ scores. As has been done in other samples with young children with autism (e.g., Lord, Risi, DiLavore, Shulman, Thurm, & Pickles, 2006), ratio based scores were used throughout this paper as the Mullen subscale T-scores commonly yielded a floor score in this sample (% with floor T score of 20: visual reception, 59%; fine motor, 72%; receptive language, 80%; expressive language, 76%).

**Vineland Scales of Adaptive Behavior, Interview Edition—**The Vineland (Sparrow, Balla, & Cicchetti, 1984) is a standardized parent interview designed to assess adaptive behavior across four domains: social, communication, daily living, and motor skills. Standard scores of these 4 domains were used as floor effects were uncommon given the wide range of normative data available for these domain scores.

# Results

## Maximum Covariance Analysis

Taxometric analyses were conducted using MAXCOV[1], which is particularly well suited for identifying overlapping dichotomous distributions embedded within a range of observed scores. In contrast to common clustering algorithms which tend to impose structure upon a

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dataset regardless whether it is continuous or discrete in nature, taxometric procedures begin with the null hypothesis that the measured traits represent continua and seek disconfirming evidence of this assumption (Beauchaine, 2003). In MAXCOV, variables are taken three at a time, and the covariance of two is calculated within adjacent intervals of the third. A smoothed regression function is then fitted through the resulting covariance values. Peaked regression functions are suggestive of discrete latent classes, whereas flat regression functions characterize continua (see Beauchaine & Marsh, in press; Waller & Meehl, 1998). In the discrete case, the location of the MAXCOV peak identifies the most efficient cut point for dividing the sample, which in turn allows for estimation of the base rates for both groups. With 4 variables for analysis (Mullen IQ scores), 12 non-redundant MAXCOV plots can be generated. When peaked functions consistently emerge within the same interval, indicating similar baserates regardless of the variable combinations used, more confidence can be placed in the identified classes as being truly discrete. Given such consistency, Bayesian-estimated group membership probabilities are calculated by combining information from each MAXCOV run. Six of the 12 conditional covariance plots indicate a sharp peak in the function indicating a low base rate taxon at the high end of the Mullen IQ score distributions. Base rate estimates based on the posterior probability of taxon membership resulted in a subgroup of high Mullen scores that comprised 17.8% of the sample.

### Latent Class Analysis

After finding evidence for discontinuity in the IQ distributions in the sample using the MAXCOV procedure, we then examined the data using latent class analysis (LCA, Lazarsfeld & Henry, 1968). LCA is a maximum likelihood based method which provides model-based parameter estimates in contrast to model-free methods such as cluster analysis. The software program, *M-plus* (Muthen & Muthen, 2004) was used to assess whether there is evidence of multiple, unobserved latent classes in this sample based on the four subscales of the Mullen. Models specifying 2, 3, and 4 latent classes were run. Variances for each class were assumed to be equal in order to minimize the number of parameters being estimated.

Results indicated that a 2 group model fit the data significantly better than a single group model (Table 1). Similarly, 3 groups fit better than 2, and 4 groups fit better than 3. No improvement in fit was seen with a 5 group model. Means on the Mullen IQ scores for the four groups identified in the 4 groups LCA solution are illustrated in Figure 1. Rather than simply reflecting overall differences in intellectual functioning these groups illustrate striking differences in both the absolute level of functioning as well as the relative abilities of the verbal and nonverbal areas. The lowest group (59% of the sample) was characterized by extremely low verbal scores as well as very low nonverbal scores with an average difference between verbal and nonverbal scores of 22 points. The second group (12.5%) was similar, however, the discrepancy between verbal and nonverbal scores in this group was even more extreme, with nonverbal scores averaging 42 points higher than verbal scores. The third group (21.7%) showed moderate to mild level of impairment with scores in the 60–70 range with verbal abilities commensurate with nonverbal abilities. The final group (7.0%) reflect a subgroup of children functioning in the average range again with verbal and nonverbal areas at roughly comparable levels. This fourth group was the only one in which the pair of verbal or nonverbal subtests showed a widely different pattern. In this group the visual reception scale was much notable higher than the fine motor scale.

[1]A second taxometric algorithm, mean above minus below a cut (MAMBAC) was also applied to the data. Because the results of these analyses were fully consistent with the results obtained from MAXCOV, the more commonly used taxometric algorithm (Haslam & Kim, 2002), only the latter are reported.

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Children in group 2, which showed the very large discrepancy between verbal and nonverbal scores, were on average nearly one year younger than the children in the other groups ($F(3,452) = 26.6$, $p < .001$). Means and standard deviations for the age in months for each group are as follows: Group 1) 45.3 (8.5); Group 2, 34.8 (6.8); Group 3, 43.5 (7.7), Group 4, 42.5 (7.0). Boys and girls were equally likely to be present in each of the 4 groups ($\chi^2 = 0.85$, $p = 0.839$). Percentage of boys and girls present in each group is as follows: Boys, groups 1 to 4: 58.6%, 12.2%, 22.4%, 6.8%; Girls, groups 1 to 4: 59.3%, 14.0%, 18.6%, 8.1%.

## Comparison between LCA and MAXCOV procedures

Although the 4 group model was found to provide the best fit of the data in the latent class analyses, we wished to compare the classification results of the 2 class LCA model with the MAXCOV results to directly compare the 2-group solution of these different methods. Both methods identified a relatively small group of higher functioning children with the 2 group LCA model placing 19.1% of the sample in this high group and MAXCOV 15.1% of the sample in this group. Overall, there was high agreement between the LCA constrained variance classification results and the MAXCOV procedure as 85.6% of individuals were classified similarly between the two approaches. Thus, 14.4% of the sample was classified differently by these two methods. When examining the combination of the LCA 2 group results and the MAXCOV results with the LCA 4 group results described above, one sees a striking similarity. Children placed in the low group by the LCA 2 group model, but placed in the high group in MAXCOV, show the same extreme difference between their verbal and nonverbal scores (Figure 2). Children in the opposite group (LCA high/MAXCOV low) show relatively equal verbal and nonverbal scores in the 60–70 range.

Figure 3 illustrates the relationship between the Mullen Verbal (mean of Receptive and Expressive Language scales) and Nonverbal (mean of Visual Reception and Fine Motor scales) IQ scores using a convex hull plot (Vidmar & Pohar, 2005). Given the substantial overlap of verbal and nonverbal scores between the groups, the convex hull for each subgroup, rather than each individual point, is displayed. Relative density plots for each variable are displayed in each margin. This plot reveals the complexities involved in categorizing young children with ASD in terms of their intellectual functioning. Clearly the “low” and “low/med” groups show strengths in nonverbal relative to their verbal performance. However, the two higher groups show more commensurate verbal and nonverbal performance. The relative density plots, nicely reveal the overlapping verbal and nonverbal distributions, however, information about the relative sample size is lost. The stacked histograms show the overall verbal and nonverbal IQ distributions broken down by LCA group membership.

The reader has noticed that the groups depicted in these plots have been assigned descriptive labels of “Low,” “Low Verbal/Med Nonverbal,” “Medium,” and “High.” Although helpful as a shorthand method to referring to these latent classes, one should not place undo emphasis on the meaning of these labels. For example, children placed in the “High” group in the LCA will not necessarily be described clinically as having “high-functioning autism.” Some children in both the “Med” and “High” groups have verbal IQ scores above 80, and some children in all but the “Low” group have nonverbal IQ scores above 80. One can see that the “Med” group in Figure 3 overlaps with every other group. Children whose scores fall into these areas of overlap have notable lower posterior probabilities of group membership. Though the mean posterior probability for group membership was .88, 24% of the sample had probabilities of less than .80, and 8% less than .60.

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### Group classification and relationship to ADI, ADOS, and Vineland

Finally, we compared the groups identified via the LCA 4 group model on the Vineland, ADI, and ADOS measures (Table 2) with ANOVA and Bonferroni post-hoc comparisons. Vineland socialization and communication domains both showed a gradation in scores consistent with the findings for the Mullen. Vineland communication scores were increasingly higher across groups 1 to 4 and socialization scores were increasingly higher across groups 1 to 3, with no difference between groups 3 and 4. On the daily living skills and motor skills domains, only group 1 had significantly lower scores compared with the other 3 groups.

The ADOS social and ADI social scores showed similar patterns in which groups 1 and 2 tended to show greater impairment (i.e., higher scores) than did groups 3 and 4. Groups 1 and 2 also showed more impairment than group 3 on the ADOS communication score. In contrast, on the ADI communication scores, groups 3 and 4 had higher scores than group 2. This likely reflects the greater number of items for which verbal children may be rated compared to nonverbal children. Finally, groups 3 and 4 had significantly higher ADI repetitive and stereotyped behaviors scores than did group 2.

Clearly, these groups differed in their adaptive behavior and symptom presentation, however, the question remains as to whether these differences simply reflect the overall relationship of verbal and nonverbal abilities to adaptive behavior and autism symptoms. To examine this question, verbal (mean of receptive and expressive language subscales) and nonverbal (mean of visual reception and fine motor subscales) IQ scores were regressed on each Vineland, ADOS, and ADI measure. Then, LCA group membership was added as a second step in the regression using 3 dichotomous indicators (variable 1 coded 1 for group 2, variable 2 coded 1 for group 3, variable 3 coded 1 for group 4 while group 1 was coded zero on all 3 variables). Table 3 shows these results in which LCA group membership added significantly to the prediction of Vineland Socialization, Communication, Daily Living Skills, and ADI Social scores above and beyond that of verbal and nonverbal IQ. This provides another line of evidence for latent classes of IQ as opposed to a single or even bivariate (namely, verbal and nonverbal) continuous dimension of IQ in young children with autism spectrum disorders.

## Discussion

Heterogeneity in autism has long been noted. Variability in IQ is routinely one of the largest contributors to this heterogeneity. The current study examined the degree to which variability in information processing, both verbal and nonverbal, may reflect unobserved or latent groups within a large sample of preschool children with ASD. Thus, rather than a single wide-ranging distribution of IQ, we sought whether there is evidence that this wide range of functioning may reflect the presence of discrete latent groups. By utilizing two different techniques, latent class analysis and taxometric analysis (Beauchaine, 2003) this study avoids some of the difficulties present in earlier work investigating subgroups in autism based on IQ. First, a taxometric analysis was employed to assess whether evidence for discrete distributions of IQ could be found. This approach did suggest discontinuity in the IQ distribution at the higher end of the Mullen scale.

This evidence in hand, we used latent class analyses to explore this question and to assess whether 2 or more latent groups based on IQ could be identified. The LCA analysis revealed a 4 group solution as providing the best fit for these data. These four groups can be described as a mixture of the overall level of functioning in the group coupled with the presence or absence of a large discrepancy between verbal and nonverbal functioning. The largest group, comprised children with low nonverbal and very low verbal scores and

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reflected those with the most severe cognitive impairments. A second group also showed very low verbal abilities but had nonverbal scores over 40 points higher on average. The third and fourth groups reflected commensurate verbal and nonverbal abilities with the third group showing mild to moderate impairments in their cognitive functioning and the fourth, highest functioning group scoring in the low average range.

Groups with identical patterns of Mullen scores were observed when contrasting the 2 group latent class analysis results with those from the MAXCOV method which yields, by definition 2 groups when evidence of taxonicity is present. Children who were classified in a similar manner with these two methods matched the lowest and highest functioning groups identified in the LCA four class model. Children classified differently across the two methods seem to comprise 2 distinct IQ-based subgroups that are different both from a simple low- or high-functioning group, as well as different from each other. The verbal versus nonverbal dimension of intellectual functioning in addition to the absolute level of overall functioning is therefore important to evaluate when considering subgroups of children with autism.

Though no sex differences were present in the likelihood of group classification, there was an intriguing mean difference in age among the groups. Children in group 2, which showed an extreme discrepancy between verbal and nonverbal scores was on average nearly 1 year younger than the children in the other groups. Beside the low verbal scores and large verbal-nonverbal discrepancy, this group also showed the lowest level of repetitive and stereotyped behaviors on the ADI. One interpretation of these findings is that group 2 may reflect a developmental or maturational effect rather than a uniquely different IQ subgroup. As children in this group age, those whose language and communication ability improve would look like those in group 3 (with more commensurate verbal and nonverbal abilities), whereas those who make slow progress would tend to resemble those in group 1 (with more profound verbal impairments). Perhaps as well, levels of repetitive behaviors may increase to levels similar to the other groups as these behaviors often follow the social and communication impairments in young children with autism. Alternatively, this group may signify a specific language impairment (SLI) in these children as described by Kjelgaard and Tager-Flusberg (2001). Whether language deficits relative to nonverbal IQ in children with autism compared with children with SLI represents the same or different underlying mechanisms is not known. However, clarifying areas of similarity and difference between children with ASD, children with other developmental disabilities, and typically developing children continues to be an important line of inquiry for understanding the genetics and underlying neurobiologic and neurocognitive mechanisms involved in autism.

This age difference in group 2 also raises an important measurement issue when working with children with moderate to severe cognitive impairments. Ratio-based IQ scores were used in this study to avoid the problem of a floor effect on low-end scores, differences in mean age among the groups (which serves as the denominator in the scores) may come in to play. For example, there may be specific items on the Mullen that tend to be particularly difficult (e.g., those requiring imitation?) or easy (e.g., those clearly requiring no spoken instruction?) for children with autism in comparison to children in the normative sample functioning at roughly the same developmental level. Simply examining age-equivalence scores rather than the ratio-based scores does not address this issue as functioning at a 20-month-old level will mean vastly different things for a 2- versus 4-year-old child.

The highest functioning group identified by the latent class analysis (group 4) had much higher mean Mullen scores (verbal IQ = 88, nonverbal IQ = 97) compared to group 3 (verbal IQ = 63, nonverbal IQ = 70). Despite this large difference in intellectual functioning these groups did not differ on the Vineland socialization, daily living skills, or motor skills domains. The average standard score across the four Vineland subdomains was 73 for group 4 and 67 for group 3 showing a much bigger relative weakness in adaptive functioning for group 4. In addition, groups 3 and 4 did not differ on any ADOS or ADI scores. Despite the striking difference in levels of cognitive functioning between groups 3 and 4, this did not translate into systematic differences in adaptive functioning or level of autism symptoms as measured by the ADOS and ADI.

We also found that LCA group membership accounted for significant proportion of the variability of Vineland socialization, communication, daily living skills, and ADI social scores beyond that accounted for by the Mullen verbal IQ and nonverbal IQ scores. This provides additional evidence of the importance of considering IQ in young children with ASD more than simply a single dimension. Indeed, the results presented here suggest that there is more than a simple linear relationship between intellectual functioning and adaptive behavior and autism symptoms, even when independently measuring both verbal and nonverbal intellectual abilities.

This study comprises a very large sample of young children who have been carefully diagnosed as being on the autism spectrum, and thus, we believe the findings here should generalize to the broader population of children with ASD in this age range. However, this sample was not collected as a population-based epidemiologic sample. Replication is clearly needed. One should be particularly cautious in making assumptions regarding the relative size of each of the IQ groups described. Of the 1,824 Mullen subscales (4 subscales X 456 children) only 11% represent scores in the “average” range (T-scores of 40 or greater, 16$^{th}$ percentile or greater). Many studies of older children with ASD report a much higher proportion in the average range of intellectual functioning. There are several issues that may bear on the representativeness of this sample. First, this sample may truly contain fewer high-functioning children with ASD than are present in the population as families who seek to participate in university studies with their preschooler with ASD may not be representative of all preschoolers with ASD. Second, these children were tested primarily between in the late 1998 and 2001 and perhaps this represents a cohort effect compared to more recent samples. Third, by assessing preschoolers and using a developmental instrument designed for use from infancy through age 5, this sample may have included a greater proportion of more impaired children than is often found in samples of older children. It is often a fine line between getting a valid estimate of a nonverbal child’s level of intellectual functioning and simply being unable to collect valid, interpretable quantitative data. Some of these children will continue to fall further and further behind their same-age peers in terms of their cognitive development. Many well-developed instruments for older children are limited in their ability to measure the low end of intellectual functioning as normative data is simply not available. Thus, there may be portion of the children in the present sample, who by virtue of the difficulties in obtaining meaningful quantitative data, may simply never take part in studies of older children with ASD.

Whether the methods used here or similar statistical methods will provide evidence for latent classes based on IQ in older children remains an open question and one that needs further study. However, careful attention needs to be paid to how the use of a given measurement instrument will impact the scores it yields (e.g., how much variability on the low end of the scale is there?) and even the resulting sample the study produces. This is particularly true when studying verbal information processing and language development in children with autism (Tager-Flusberg, 2000). The likelihood that a sample of preschoolers with autism, when assessed five or ten years later, will present an even wider range of functioning than they did at the outset makes the identification and measurement of the underlying neurocognitive mechanisms at work in autism that much more difficult.. In this pursuit, we must be aware of how our measurement tools, presumably impartial and objective, may also



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become construction tools that actively shape and influence the phenomenon we wish to study. Any seasoned child assessor knows, a la Heisenberg, that “observing” a child at a table with an open briefcase full of booklets and blocks can have a profound influence on what we end up measuring.

In summary, by examining a large, well-characterized sample of preschool children with ASD, these findings provide an important evidence of the presence of multiple IQ-based subgroups within autism. Four latent classes were identified, that represent a very different levels of intellectual functioning as well as different patterns of relative verbal versus nonverbal abilities. Group membership was found to relate to adaptive functioning and social impairment, above and beyond the direct relationship of verbal and nonverbal IQ. Cross-sectional samples such as this must be complemented with longitudinal data as variability in course represents yet another area of heterogeneity in autism where much remains to be learned.

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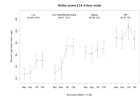


**Figure 1.**
Mean Mullen IQ scores of latent groups.



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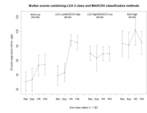


**Figure 2.**
Mean Mullen scores of latent groups by combining classification methods.



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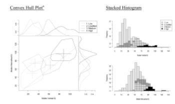

**Figure 3.**

Convex Hull Plots and Histograms of Mullen Verbal and Nonverbal scores by LCA groups. a. Marginal distributions reflect relative density plots for each group. Each cross reflects the bivariate group mean +/− 1 SD. The diagonal line depicts equivalent verbal and nonverbal IQ.

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**Table 1**

Latent Class Analysis Fit Indices.

| Number of Classes | BIC | Entropy | Logliklihood | Lo-Mendel- Rubin value | Lo-Mendel- Rubin p- value |
|---|---|---|---|---|---|
| One | | | 897.0 | | |
| Two | −1882.3 | 0.840 | 1017.7 | 237.8 | 0.005 |
| Three | −1886.4 | 0.690 | 1053.4 | 70.4 | 0.038 |
| Four | −1892.5 | 0.773 | 1090.1 | 68.8 | 0.029 |
| Five | −1850.9 | 0.748 | 1103.0 | 73.9 | 0.369 |

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## Table 2

Vineland, ADI, and ADOS scores by LCA group

| | 1. Low | | 2. Low Verbal/ Med Nonverbal | | 3. Medium | | 4. High | | | Post-hoc Bonferroni comparisons[a] | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | 1vs | 1vs | 1vs | 2vs | 2vs | 3vs |
| | M | SD | M | SD | M | SD | M | SD | F | 2 | 3 | 4 | 3 | 4 | 4 |
| Vineland | | | | | | | | | | | | | | | |
| Socialization | 57.6 | (6.4) | 60.1 | (9.0) | 65.2 | (8.4) | 66.8 | (10.0) | 37.72 | 1<2 | 1<3 | 1<4 | 2<3 | 2<4 | |
| Communication | 54.0 | (6.8) | 58.6 | (5.3) | 67.3 | (8.2) | 77.9 | (12.8) | 131.06 | 1<2 | 1<3 | 1<4 | 2<3 | 2<4 | 3<4 |
| Daily living skills | 57.2 | (7.8) | 65.3 | (6.8) | 64.0 | (8.3) | 67.4 | (8.4) | 35.01 | 1<2 | 1<3 | 1<4 | | | |
| Motor skills | 63.2 | (14.2) | 77.8 | (16.9) | 72.1 | (12.9) | 81.7 | (16.7) | 27.41 | 1<2 | 1<3 | 1<4 | | | |
| ADOS | | | | | | | | | | | | | | | |
| Social | 11.4 | (2.1) | 11.5 | (2.1) | 9.2 | (2.5) | 8.5 | (2.7) | 35.80 | | 1>3 | 1>4 | 2>3 | 2>4 | |
| Communication | 6.5 | (1.4) | 6.5 | (1.5) | 5.7 | (1.6) | 5.8 | (1.6) | 8.57 | | 1>3 | | 2>3 | | |
| ADI | | | | | | | | | | | | | | | |
| Social | 20.1 | (4.7) | 18.7 | (3.9) | 17.1 | (4.9) | 15.7 | (5.0) | 16.00 | | 1>3 | 1>4 | | 2>4 | |
| Communication | 11.9 | (2.3) | 11.2 | (2.2) | 12.5 | (4.1) | 13.3 | (3.7) | 4.68 | | | | 2<3 | 2<4 | |
| Repetitive | 5.1 | (1.8) | 4.3 | (1.7) | 5.4 | (2.2) | 5.9 | (2.8) | 5.40 | | | | 2<3 | 2<4 | |

[a]cell values indicate significant pairwise group differences at $p < .05$

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## Table 3

Linear Regression Analyses Predicting Vineland, ADI, and ADOS from Mullen IQ and LCA Group.

| | Step 1 | | | Step 2 | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Verbal IQ | Nonverbal IQ | | Verbal IQ | Nonverbal IQ | Grp 2 | Grp 3 | Grp 4 |
| | $R^2$ | β (t) | β (t) | $\Delta R^2$ | Δ (t) | Δ (t) | Δ (t) | Δ (t) | Δ (t) |
| Vineland | | | | | | | | | |
| Socialization | .69*** | 0.75 (19.49***) | 0.11 (2.94**) | .008* | 0.91 (14.19***) | 0.07 (1.54) | 0.05 (1.38) | −0.1 (−2.23*) | −0.11 (−2.22*) |
| Communication | .31*** | 0.46 (8.29***) | 0.12 (2.18*) | .035*** | 0.71 (7.86***) | 0.18 (2.65**) | −0.03 (−0.70) | −0.17 (−2.55*) | −0.34 (−4.71***) |
| Daily living skills | .38*** | 0.04 (0.67) | 0.59 (10.73***) | .027*** | 0.23 (2.59**) | 0.59 (8.89***) | 0.04 (0.75) | −0.08 (−1.25) | −0.25 (−3.53***) |
| Motor skills | .319*** | −0.04 (−0.76) | 0.59 (10.40***) | .013+ | 0.13 (1.36) | 0.57 (8.06***) | 0.04 (0.84) | −0.1 (−1.36) | −0.17 (−2.24*) |
| ADOS | | | | | | | | | |
| Social | .249*** | −0.59 (−10.13***) | 0.14 (2.39*) | .003 | −0.56 (−5.85***) | 0.12 (1.66) | 0.01 (0.11) | −0.04 (−0.63) | 0.02 (0.33) |
| Communication | .061*** | −0.30 (−4.56***) | 0.07 (1.15) | .006 | −0.28 (−2.56*) | 0.06 (0.81) | −0.02 (−0.34) | −0.07 (−0.86) | 0.04 (0.44) |
| ADI | | | | | | | | | |
| Social | .166*** | −0.40 (−6.61***) | 0.00 (−0.08) | .019* | −0.65 (−6.45***) | 0.04 (0.50) | −0.06 (−1.13) | 0.16 (2.11*) | 0.20 (2.60**) |
| Communication | .044*** | 0.30 (4.55***) | −0.23 (−3.56***) | .008 | 0.19 (1.72) | −0.26 (−3.21**) | 0.01 (0.20) | 0.07 (0.88) | 0.15 (1.84) |
| Repetitive | .032*** | 0.25 (3.82***) | −0.20 (−3.06**) | .013 | 0.08 (0.70) | −0.17 (−2.13*) | −0.05 (−0.94) | 0.09 (1.17) | 0.16 (1.92) |