

‘Subtypes’ in the Presentation of Autistic Traits in the General Adult Population

Colin J. Palmer · Bryan Paton · Peter G. Enticott · Jakob Hohwy

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Abstract The present study examined the presentation of autistic traits in a large adult population sample ($n = 2,343$). Cluster analysis indicated two subgroups with clearly distinguishable trait profiles. One group ($n = 1,059$) reported greater social difficulties and lower detail orientation, while the second group ($n = 1,284$) reported lesser social difficulties and greater detail orientation. We also report a three-factor solution for the autism-spectrum quotient, with two, related, social-themed factors (Sociability and Mentalising) and a third non-social factor that varied independently (Detail Orientation). These results indicate that different profiles of autistic characteristics tend to occur in the adult nonclinical population. Research into nonclinical variance in autistic features may benefit by considering social- and detail-related trait domains independently.

Keywords Autistic traits · Autism-spectrum quotient · Cluster analysis · Subgroups · Factor analysis

C. J. Palmer (✉) · B. Paton · J. Hohwy
Cognition and Philosophy Lab, Philosophy Department, Monash University, Clayton, Melbourne, VIC 3800, Australia
e-mail: Colin.Palmer@monash.edu

B. Paton
Monash Biomedical Imaging, Monash University, Clayton, Melbourne, VIC 3168, Australia

B. Paton
School of Psychological Sciences, Monash University, Clayton, Melbourne, VIC 3800, Australia

P. G. Enticott
Cognitive Neuroscience Unit, School of Psychology, Deakin University, Melbourne, Australia

Introduction

A central feature of autism spectrum disorder (ASD) is the range in symptom severity: both within the *clinical* population, contributing to heterogeneity amongst individuals with ASD, and, of particular interest here, encompassing the *general* population (Lai et al. 2013; American Psychiatric Association 2013). This latter impression comes primarily from research that has recorded the prevalence of ASD-like features across large community samples. Significantly, the extent to which the relevant traits are reported in the community appears to vary continuously and with normal or skewed-unimodal distribution (e.g., Baron-Cohen et al. 2001; Constantino and Todd 2003; Posserud et al. 2006; Hurst et al. 2007). This contrasts, for example, with discontinuity or bimodality in trait distribution, either of which could set the clustering of symptoms in ASD apart as a matter of type rather than degree. Moreover, there is evidence for overlap in the genetic bases of ASD-like traits in the nonclinical population and ASD symptoms in the clinical population (Chakrabarti et al. 2009; Bolton et al. 1994; Piven et al. 1997; Robinson et al. 2011).

A recent surge in cognitive and neuroscientific research builds on these findings by comparing nonclinical adults in their degree of ASD-like traits as an approach to studying the mechanisms underlying this condition. This has included studies examining visual search (e.g., Grinter et al. 2009a, b), visual illusion susceptibility (Walter et al. 2009), biological motion processing (van Boxtel and Lu 2013), multisensory integration (Palmer et al. 2013; Donohue et al. 2012), social attention (Freeth et al. 2013a; Nummenmaa et al. 2012), gaze responses (Bayliss and Tipper 2005; Chen and Yoon 2011) and neurophysiological characteristics (Jakab et al. 2013; Puzzo et al. 2010;

Nummenmaa et al. 2012; Sutherland and Crewther 2010). These studies most commonly use the autism-spectrum quotient (AQ), an inventory measure designed for use with adult community samples as either a screening or research tool (Baron-Cohen et al. 2001). The AQ necessarily assesses a range of social (e.g., sociability, mentalising) and non-social (e.g., restricted interests, detail-focus) attributes, and researchers have typically compared individuals on their total AQ score or subscale scores, each produced by summing across items that assess more specific behaviours or characteristics.

It is an open question, however, regarding the extent to which autism can be conceived of as a *singular* construct that varies across the general population. A ‘unitary spectrum’ model such as this conflicts with a suggestion by Happé, Ronald and colleagues that distinct genetic, neurological and cognitive causes may underlie the symptoms of ASD (Happé et al. 2006; Happé and Ronald 2008; see also Mandy and Skuse 2008). This alternate approach has been labelled the ‘fractionable autism triad’ hypothesis—in reference to the three symptom domains of impaired social interaction, impaired communication and restricted behaviours/interests specified for Autistic disorder in the DSM-IV (American Psychiatric Association 2000) and ICD-10 (World Health Organization 2004). (This model is still relevant to, and in some respects better represented by, the diagnostic criteria set out for ASD in the current 5th edition of the DSM, however; American Psychiatric Association 2013).

The evidence that separate etiologies underlie the three DSM-IV symptom domains comes most notably from research into the relationship between ASD-like characteristics in the community, employing large-scale childhood twin samples (Robinson et al. 2012; Ronald et al. 2006, 2005, 2006b, Ronald et al. 2011). While symptoms in the three domains co-occur at a level above chance (Happé and Ronald 2008; see Mandy and Skuse 2008 for review), low to moderate (rather than strong) correlations are observed between these characteristics. In addition, similarly modest overlap is estimated between the heritability of each domain, and, finally, individual symptoms can sometimes occur strongly in the absence of other cardinal features of ASD. A recent review of factor analytic studies involving clinical ASD participants concluded support for two distinct social and non-social dimensions underlying inventory measures of ASD symptoms—again suggesting that a conception of autism as a unitary construct is insufficient (Shuster et al. 2013). Multi-factor solutions are similarly reported for nonclinical samples (e.g., Austin 2005).

The idea here is that ASD trait domains vary independently to a marked degree across the population—with a diagnosis of ASD applied in cases where these characteristics happen to co-occur strongly. In principle, two individuals with the same AQ score, for instance, may still

have a different *profile* of ASD-like traits, with corresponding cognitive and neurological dissimilarities. The present study aimed to build on the discussed literature by examining how profiles of ASD-like characteristics, as assessed by the AQ, tend to manifest in the general adult population. We used cluster analysis to examine the presentation of AQ item scores in a large sample recruited online. This statistical method finds the optimal manner of grouping cases (here, individuals) based on their similarity across a range of variables (here, the items of the AQ); in other words, this technique allowed us to discover patterns of trait presentation that tend to occur in the population. We also performed a factor analysis (as has been done previously for the AQ; e.g., Austin 2005) to provide a more complete picture of the relationship between constructs underlying the AQ and how these constructs differ between individuals.

To our knowledge, this is the first study to look specifically at nonclinical variation in ASD-like traits in adults with cluster analysis, and one of the first to apply this technique to the AQ. The presentation of autistic traits in the adult population is important to clarify, due in part to the developmental nature of ASD and the present trend in research that focuses on nonclinical adult samples. Cluster analysis has been performed previously using the AQ with a high-functioning adult clinical group: Ring et al. (2008) report that their sample comprised between two and four clusters of individuals that varied in the severity of symptoms but not in their symptom profile. Ring et al. (2008) note that this clustering supports a unitary spectrum (or ‘severity gradient’) characterisation of the heterogeneity in this clinical group, such that individuals are best grouped according to their overall magnitude of traits rather than in their profile of characteristics. Similarly, we can hypothesise that, if a unitary spectrum account best describes the presentation of ASD-like characteristics in the general adult population, cluster analysis will reveal either a single cluster (i.e., no subgroups) or multiple clusters that differ in mean item or domain scores, but not in their profile of responses across the different traits that the AQ assesses. In contrast, the fractionable triad hypothesis allows for the possibility that the presentation of autistic traits in the general population is best characterised in terms of subgroups with different trait profiles.

Methods

Participants

The sample comprised 2,343 adults who completed the AQ via an online survey platform ($M = 31.36$, $SD = 11.17$ years; 47.8 % female; 86.6 % right handers, 10.7 % left handers;

88.0 % indicating some degree of tertiary education). A link to the study was displayed in the Amazon Mechanical Turk system, and participation was restricted to individuals who identified as over 18 years in age and with current residence in the United States. Forty individuals who did not complete the survey and 63 individuals who shared an IP address with a previous participant were excluded prior to data analysis. Each participant received 1.50 USD upon completion of the study. Ethical approval for the study was obtained from the Monash University Human Research Ethics Committee. All participants gave informed consent.

AQ

The AQ is a 50-item self-administered questionnaire designed to assess both cardinal and associated traits of ASD in either clinical or nonclinical populations (Baron-Cohen et al. 2001). Each item consists of a statement (e.g., “When I’m reading a story, I find it difficult to work out the characters’ intentions”) that respondents rate in terms of personal applicability on a 4-point Likert scale (“definitely agree”, “slightly agree”, “slightly disagree”, “definitely disagree”). In the present study, we used Likert scoring (4-3-2-1) rather than the more common binary scoring method (1-1-0-0), as the former may better capture individual variability in responses and is more suitable for the analysis techniques employed here. Scores using this method can range 50–200 overall, or 10–40 for each of five subscales. Subscales are theoretically defined, consist of ten items each, and are labelled Social Skills, Imagination, Communication, Attention to Detail and Attention Switching. Twenty-six items in the AQ are reverse scored, such that higher scores indicate greater resemblance to the symptoms of ASD for all items. Individuals with a diagnosis of ASD score significantly higher than nonclinical samples on both total AQ and individual subscales (Baron-Cohen et al. 2001; Broadbent et al. 2013; Hoekstra et al. 2008; Lau et al. 2013b). The test–retest reliability and internal consistency of this scale have each been evaluated as within an acceptable range (Baron-Cohen et al. 2001; Broadbent et al. 2013; Hoekstra et al. 2008; Lau et al. 2013b).

Factor Analysis

An exploratory factor analysis (EFA) was conducted across the 50 items of the AQ using the maximum likelihood method of factor extraction. EFA employs a common factor analysis model as distinct from Principle Components Analysis. Promax (oblique) rotation was applied, bearing in mind that the traits that this questionnaire is designed to assess are expected to covary to an extent (Austin 2005). EFA was performed from 1 to 10 maximum

factors, and the factor solution that minimised the Akaike information criterion (AIC) was selected for further examination. AIC is preferred to significance testing here because the former weights the log likelihood evidence for each factor solution by the number of factors (model complexity). The scree plot, Kaiser’s criterion, and parallel analysis were also examined for agreement with the AIC method in the number of factors to extract. The scree plot involves plotting the eigenvalues for each factor and retaining factors to the left of the point of inflexion. Kaiser’s criterion involves retaining factors with eigenvalues greater than 1 (these methods, including their potential deficiencies, are reviewed in Field 2009; Ledesma and Valero-Mora 2007). Parallel analysis compares eigenvalues of each factor against the 95th percentile of eigenvalues obtained from a set of control samples. In the present application, we used 1,000 control samples that were permutations of the original data. The permutation method and other details are described further in O’Connor (2000, 2014). Factor scores for each participant were derived using ridge regression. Confidence intervals (95 %) for item factor loadings were obtained via exhaustive delete-one jackknife resampling. Items that loaded on a given factor with a lower confidence bound greater than 0.4 were examined for factor interpretation, as this indicates at least 16 % shared variance between the item and factor (Stevens 2009). Cronbach’s unstandardized alpha was calculated to assess internal consistency of the entire questionnaire and item subsets identified for each factor.

Cluster Analysis

Clustering of the sample was investigated with cases characterised by responses across the 50 items of the AQ. Proximity between cases was quantified in terms of Spearman’s rank correlation coefficient, and clusters were formed via hierarchical agglomerative clustering with complete linkage (consistent with Ring et al. 2008). Martinez et al. (2011) recommends examining data clustering with the use of several distance and clustering methods: in the current dataset, the number of clusters observed did not differ when instead employing the Euclidean distance dissimilarity measure or Ward’s and weighted average linkage methods.

The gap statistic method was used to determine whether or not clustering was apparent in the data and to estimate the number of clusters present (Tibshirani et al. 2001; Martinez et al. 2011). Participant data was first clustered separately for 1–10 clusters such that the within-cluster dispersion for each of these clustering outcomes could be calculated. Reference distributions were then generated as uniform distributions across the range of participant data for each variable. For each number of clusters (1–10), 10 reference distributions

were created and underwent clustering. The average within-cluster dispersion of the 10 reference distributions for each number of clusters was calculated to form the dispersion expected if no real clustering was present in the data. The gap statistic for each cluster number is the difference between the observed and expected dispersions. The number of clusters in the participant data is taken as the smallest number of clusters that satisfies that criteria $gap(k) \geq gap(k + 1) - s_{k+1}$, where gap is the gap statistic, k is the number of clusters, and s the (weighted) standard deviation of the within-cluster dispersion of the ten reference distributions. This procedure followed Tibshirani et al. (2001) and Martinez et al. (2011), and was run using MATLAB code adapted from the latter.

Gaussian mixture modelling was also applied to examine whether the number of clusters observed using the above techniques could be reproduced using a different method. This technique employs a generative variational Bayesian modelling procedure to find a set of Gaussian densities that best predict the observed data. It minimises a free energy quantity to determine the optimal number of clusters. This involves maximizing the negative log evidence for the model given the data. This procedure was run using MATLAB code provided by Daunizeau et al. (2014).

To characterise the observed clusters, mean scores for each item of the AQ were plotted for each cluster. Confidence intervals (95 %) of item mean scores were computed using the jackknife resampling method. The proportion of items that matched a consistent severity gradient across clusters was examined for each subscale. Total AQ score, subscale scores, factor scores, and demographic characteristics (gender, age, handedness, and education level) were also compared between clusters using independent samples t tests or Chi square tests for independence (with Yates Continuity Correction for 2×2 contingency tables).

Data analysis was conducted in MATLAB, version R2012a (7.14.0.739).

Results

AQ Score Distribution

The mean total AQ score was 114 ($SD = 14.5$; median = 114; median absolute deviation = 10), corresponding to a mean binary total score of 20 ($SD = 6.9$; median = 20; median absolute deviation = 5). The distribution of total AQ scores is shown in Fig. 1.

Factor Analysis

Akaike information criterion values and variance accounted for by each factor solution are shown in Table 1. The factor solution that minimised the AIC comprised 3 factors

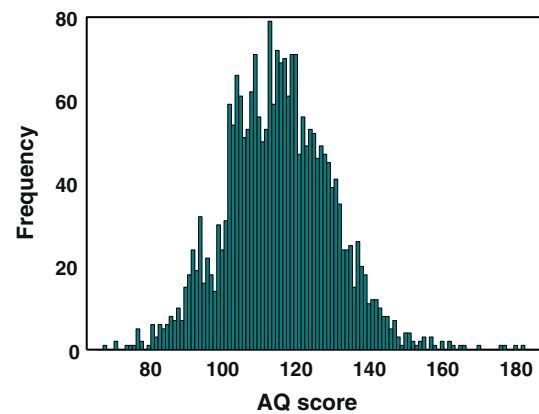


Fig. 1 Distribution of total AQ scores across the full sample ($n = 2,343$)

Table 1 AIC values and variance explained for factor solutions 1–10

Number of factors	AIC value	Variance accounted for
1	18.00	15.70
2	15.48	21.43
3	13.77	26.99
4	14.20	29.00
5	15.00	31.50
6	16.15	33.39
7	17.39	35.27
8	18.92	36.49
9	20.48	38.29
10	22.10	40.21

and accounted for 27 % of the variance. The scree plot, shown in Fig. 2, also supported extraction of 3 factors. In contrast, Kaiser's criterion indicated 5 factors, while parallel analysis indicated 16 factors. Previous research using similar datasets has also noted over-extraction of factors when using parallel analysis (e.g., Stewart and Austin 2009). The AIC method is preferable because it takes into account model evidence and model complexity. Thus, together there was strongest support for the three-factor solution. Items that loaded above threshold on each factor are shown in Table 2. A very clear pattern in item content can be seen such that the three factors correspond, respectively, to reduced sociability (reduced social skills or social discomfort), reduced mentalising (difficulty in mental-state attribution) and detail orientation.

The two social-themed factors shared a moderate positive association, but correlated very weakly in the negative direction with the Detail Orientation factor (Table 3). The associations between factor scores and the theoretically-defined subscales of the AQ (Baron-Cohen et al. 2001)

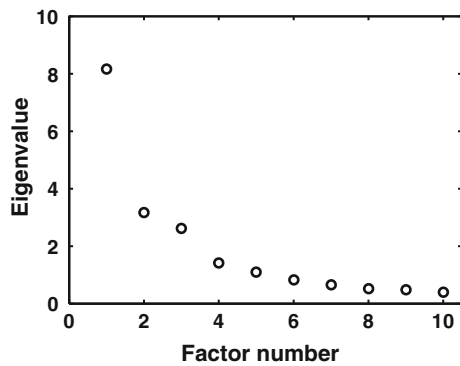


Fig. 2 Scree plot for exploratory factor analysis with common factor analysis model

demonstrated a similar pattern (Table 4). Specifically, the Sociability and Mentalising factors shared mostly moderate and strong positive correlations with the three social-themed subscales (Social Skills, Imagination, Communication) and the Attention-Switching subscale, but correlated negatively with the Attention to Detail subscale. In contrast, the Detail Orientation factor correlated strongly in the positive direction with the Attention to Detail subscale, but showed very weak correlations with the other four subscales. Similarly, the social subscales of the AQ tended to vary together moderately or strongly, but shared weak negative relationships with the Attention to Detail subscale (Table 5). The association between the Attention Switching and social domains of the AQ has been reported previously in the literature (Lau et al. 2013; Murray et al. 2013; Stewart and Austin 2009). This (perhaps counterintuitive) finding is discussed further in the Discussion.

The three factors identified each had high internal consistency ($\alpha_{\text{SOCIABILITY}} = .90$, $\alpha_{\text{MENTALISING}} = .74$, $\alpha_{\text{DETAIL ORIENTATION}} = .75$), as did the full questionnaire ($\alpha_{\text{AQ}} = .84$). The distribution of factor scores was approximately normal for each factor (see Fig. 3).

Females scored slightly higher on (reduced) Sociability than males, indicating that females were *less* sociable on average ($M_{\text{FEMALES}} = 0.04$, $SD_{\text{FEMALES}} = 1.02$; $M_{\text{MALES}} = -0.04$, $SD_{\text{MALES}} = 0.92$), $t(2,260) = -2.05$, $p < .05$, $r = .04$. In contrast, males scored higher than females on (reduced) Mentalising ($M_{\text{MALES}} = 0.12$, $SD_{\text{MALES}} = 0.93$; $M_{\text{FEMALES}} = -0.13$, $SD_{\text{FEMALES}} = 0.92$), $t(2,341) = 6.45$, $p < .001$, $r = .13$, and Detail Orientation ($M_{\text{MALES}} = 0.09$, $SD_{\text{MALES}} = 0.86$; $M_{\text{FEMALES}} = -0.10$, $SD_{\text{FEMALES}} = 0.94$), $t(2,275) = 4.93$, $p < .001$, $r = .10$. Previous research has also tended to find that males score more highly in the AQ than females (e.g., Baron-Cohen et al. 2001); however, the effect sizes for the differences in factor scores between females and males in the present study are small.

Table 2 Item loadings for three-factor solution

Item content	Loading
<i>Factor 1: sociability</i>	
I am good at social chit-chat [†]	0.83
I find social situations easy [†]	0.81
I enjoy social chit-chat [†]	0.80
I enjoy social occasions [†]	0.80
I enjoy meeting new people [†]	0.79
I find it hard to make new friends	0.63
I find myself drawn more strongly to people than to things [†]	0.59
New situations make me anxious	0.56
I would rather go to a library than a party	0.55
I frequently find that I don't know how to keep a conversation going	0.55
I prefer to do things with others rather than on my own [†]	0.48
<i>Factor 2: mentalising</i>	
I find it difficult to work out people's intentions	0.63
When I'm reading a story, I find it difficult to work out the characters' intentions	0.63
I find it easy to work out what someone is thinking or feeling just by looking at their face [†]	0.53
I find it easy to "read between the lines" when someone is talking to me [†]	0.51
When I'm reading a story, I can easily imagine what the characters might look like [†]	0.50
I know how to tell if someone listening to me is getting bored [†]	0.47
<i>Factor 3: detail orientation</i>	
I notice patterns in things all the time	0.63
I usually notice car number plates or similar strings of information	0.59
I am fascinated by numbers	0.57
I am fascinated by dates	0.55
I tend to notice details that others do not	0.53
I like to collect information about categories of things (e.g. types of car, types of bird, types of train, types of plant, etc.)	0.51

Items with lower CI exceeding 0.4 loading threshold are shown

[†] Symbol indicates reverse-scored items

Table 3 Factor intercorrelations

	Mentalising	Detail Orientation
Sociability	.48*	-.09*
Mentalising		-.14*

Pearson's linear correlation coefficients are shown. Bonferroni correction was applied to the alpha level

* $p < .0001$ (two-tailed)

Cluster Analysis

The gap statistic procedure indicated two clusters of individuals within the sample (C1, C2; see Fig. 4 for

Table 4 Correlations between factor scores and AQ subscales

	Total score	Social skill	Imagination	Communication	Attention to detail	Attention switching
Sociability	0.79* [0.78, 0.81]	0.93* [0.93, 0.94]	0.27* [0.23, 0.30]	0.69* [0.67, 0.71]	-0.11* [-0.15, -0.07]	0.61* [0.58, 0.63]
Mentalising	0.72* [0.70, 0.74]	0.59* [0.56, 0.61]	0.68* [0.66, 0.70]	0.78* [0.76, 0.80]	-0.28* [-0.32, -0.24]	0.52* [0.49, 0.55]
Detail Orientation	0.28* [0.25, 0.32]	-0.08* [-0.12, -0.04]	0.00 [-0.04, 0.04]	0.11* [0.07, 0.15]	0.84* [0.83, 0.85]	0.04 [0.00, 0.08]

Pearson's linear correlation coefficients are shown with lower and upper bounds of the 95 % confidence interval in square brackets. Bonferroni correction was applied to the alpha level

* $p < .0001$ (two-tailed)

Table 5 Intercorrelations between AQ subscales

	Social skill	Imagination	Communication	Attention to detail	Attention switching
Total score	0.81* [0.80, 0.82]	0.58* [0.56, 0.61]	0.81* [0.80, 0.83]	0.20* [0.16, 0.24]	0.70* [0.68, 0.72]
Social skill		0.32* [0.28, 0.35]	0.69* [0.67, 0.71]	-0.13* [-0.17, -0.09]	0.55* [0.52, 0.58]
Imagination			0.41* [0.37, 0.44]	-0.05 [-0.09, 0.00]	0.23* [0.19, 0.27]
Communication				-0.09* [-0.13, -0.05]	0.50* [0.47, 0.53]
Attention to detail					-0.09* [-0.13, -0.05]

Pearson's linear correlation coefficients are shown with lower and upper bounds of the 95 % confidence interval in square brackets. Bonferroni correction was applied to the alpha level

* $p < .0001$ (two-tailed)

dendrogram plot). Figure 5 shows the observed dispersion, expected dispersion and gap statistic for 1–10 clusters. As can be seen, a single maximum occurs for the gap statistic at two clusters. The values of $gap(k) - gap(k + 1) - s_{k+1}$ for $k = 1-9$ were: -0.63, 0.05, 0.09, 0.08, 0.09, 0.10, 0.13, 0.13, 0.13. The smallest number of clusters that satisfied the criteria $gap(k) \geq gap(k + 1) - s_{k+1}$ was two, indicating two clusters in the data. The two clusters were of roughly equal size ($n_{C1} = 1,059$; $n_{C2} = 1,284$). The Gaussian mixture modelling procedure indicated that a two-cluster model minimized free energy, providing supporting evidence that the correct number of clusters was obtained.

There was a small, significant association between gender and cluster status, $\chi^2(1, n = 2,343) = 21.10$, $p < 0.001$, $\phi = -0.10$, with a greater proportion of females in C1 (53.1 %) than C2 (43.5 %). Individuals in C1 ($M = 32.16$, $SD = 11.78$ years) were also marginally older on average than those in C2 ($M = 30.69$, $SD = 10.60$ years), $t(2,152) = 3.15$, $p < .01$, $r = .07$. There was a very weak association between education level and cluster status, $\chi^2(1, n = 2,343) = 5.30$, $p < .05$, $\phi = .05$, with a slightly greater proportion of respondents indicating some degree of tertiary education in C2 (89.4 %)

than in C1 (86.2 %). Finally, there was no significant association between handedness and cluster status, $\chi^2(2, n = 2,343) = 2.04$, $p = .36$, Cramer's $V = .03$ (C1: 86.9 % right handers, 11.0 % left handers; C2: 86.4 % right handers, 10.5 % left handers). In summary, the two clusters differed little in these four demographic characteristics, given the very weak effect sizes and the contribution of large sample sizes to the statistical significance of these comparisons. Thus, clusters were defined mainly in terms of autism-related features (as described below) rather than demographic characteristics.

The profile of mean scores across the 50 items of the AQ is shown for each cluster in Fig. 6. As can be seen, C1 typically scored higher than C2 on items that comprise the three social subscales (C1 > C2 for all Social Skill items, six out of ten Imagination items, and seven out of ten Communication items) and the Attention Switching subscale (C1 > C2 for seven out of ten items). In contrast, C2 scored higher than C1 for nine out of ten items that comprise the Attention to Detail subscale. The pattern of C1 scoring higher than C2 in social-themed characteristics (impairments) but lower in detail-themed characteristics is also apparent in the comparison of subscale scores and

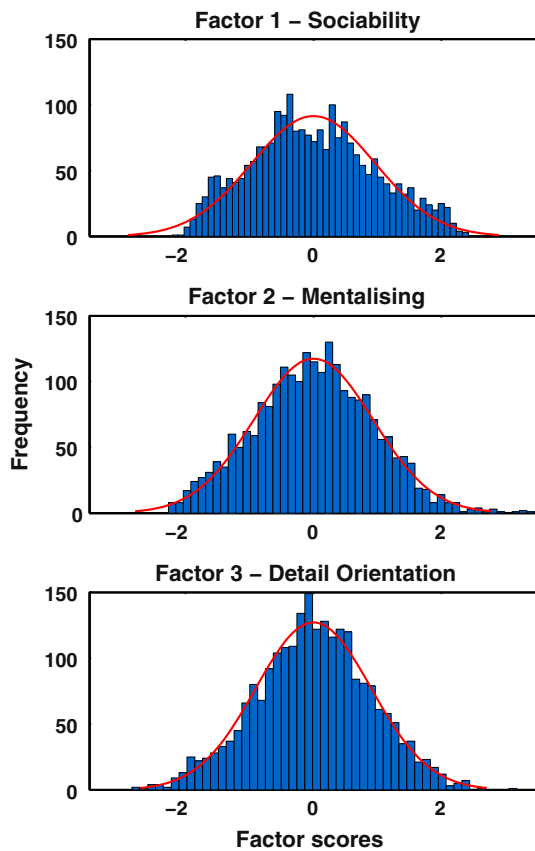


Fig. 3 Distribution of factor scores across the full sample ($n = 2,343$). Gaussian distribution fits are shown

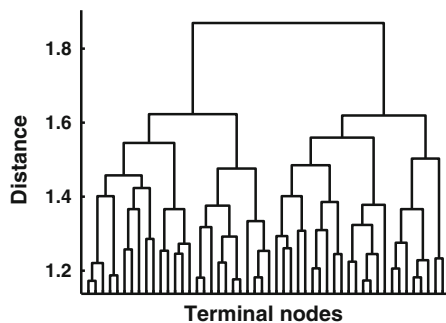


Fig. 4 Dendrogram plot with 50 terminal nodes. Hierarchical agglomerative clustering with Spearman’s proximity and complete linkage was applied to the sample with cases characterised by scores on the 50 items of the AQ

factor scores across clusters in Table 6. The effect sizes for comparisons of AQ subscale scores and factor scores between the two cluster groups were most commonly in the moderate range, as reported in Table 6. As can be seen, C1 also scored higher in total AQ than C2 (scoring higher on 60 % items in the questionnaire).

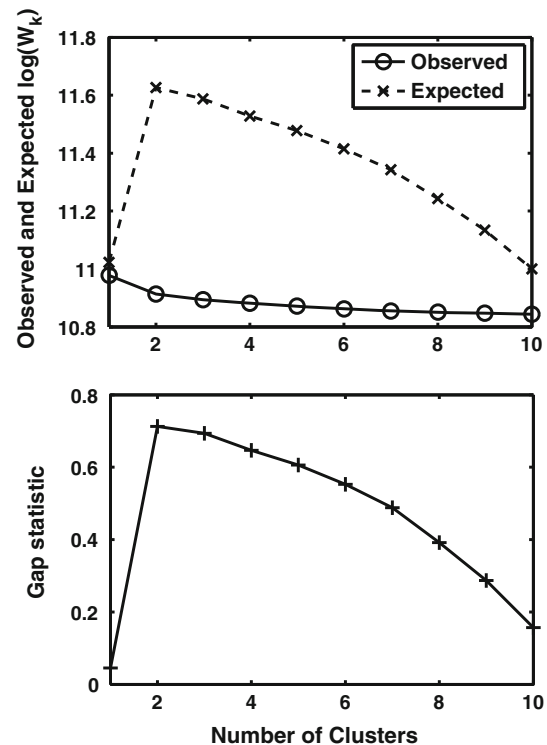


Fig. 5 The gap statistic procedure indicated two clusters within the sample. The *upper plot* shows observed and expected dispersion measures for clustering with 1–10 clusters. The *lower plot* shows the gap statistic for clustering with 1–10 clusters, with a maximum at two clusters

Discussion

The present study provides evidence for two patterns of subclinical ASD-like traits in the general adult population. In particular, cluster analysis indicated a group of respondents characterised by greater social difficulties and weaker detail-orientation, and a second group featuring better social abilities and stronger detail-orientation. This conflicts with a unitary spectrum model of autistic traits, which predicts either clustering based on symptom severity alone or an absence of subsets within the sample. (On the other hand, our results suggest that social characteristics—mentalising and sociability—do vary together to a moderate extent, and show a consistent severity gradient across the two subgroups identified). Clinical individuals score higher than controls on *all* subscales of the AQ (Baron-Cohen et al. 2001; Broadbent et al. 2013; Hoekstra et al. 2008; Lau et al. 2013b), suggesting that the differences in profile between clusters reported in the present study cannot be explained as simply indicating that detail-orientation traits are extraneous to ASD. Rather, our findings accord with a view that social and detail-orientation characteristics related to ASD tend not to co-occur in the adult population—to the extent that nonclinical individuals are best grouped in

Fig. 6 Profile of mean AQ item scores for each cluster with 95 % CI

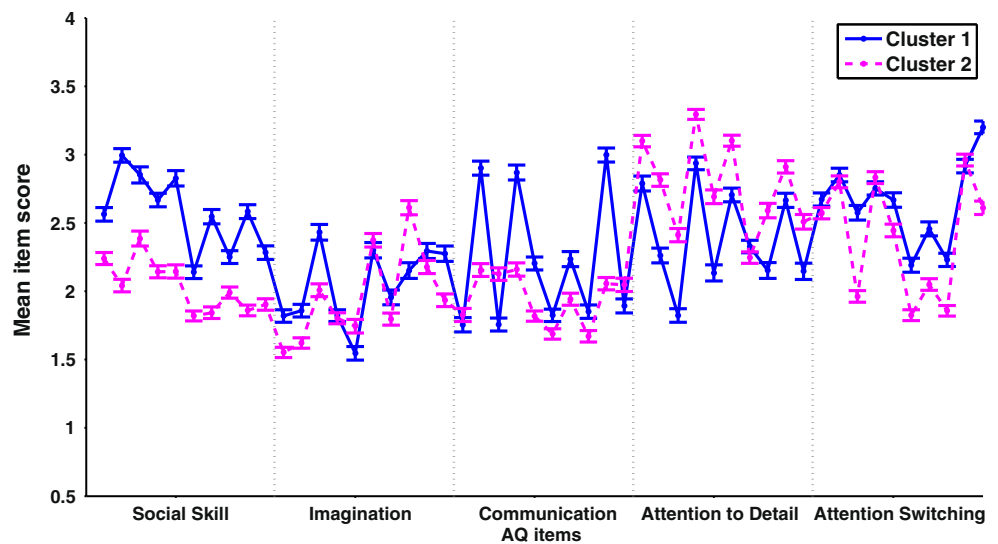


Table 6 Comparison of AQ subscale scores and factor scores across clusters

Variable	Cluster 1 <i>M</i> (<i>SD</i>)	Cluster 2 <i>M</i> (<i>SD</i>)	<i>t</i> (<i>df</i>)	<i>r</i>
<i>Cluster 1 mean > Cluster 2 mean</i>				
Total AQ	118.88 (14.74)	111.05 (13.28)	13.39 (2,151)	0.28*
Social skill	25.70 (5.09)	20.37 (4.75)	26.02 (2,192)	0.49*
Imagination	20.45 (4.25)	19.61 (3.83)	4.93 (2,154)	0.11*
Communication	22.28 (4.40)	19.48 (4.35)	15.43 (2,341)	0.30*
Attention switching	26.51 (4.23)	23.91 (3.84)	15.43 (2,161)	0.32*
Sociability	0.56 (0.85)	−0.46 (0.80)	29.99 (2,199)	0.54*
Mentalising	0.29 (0.90)	−0.24 (0.88)	14.28 (2,341)	0.28*
<i>Cluster 2 mean > Cluster 1 mean</i>				
Attention to Detail	23.94 (4.45)	27.67 (4.05)	−21.02 (2,162)	0.41*
Detail Orientation	−0.42 (0.86)	0.35 (0.78)	−22.35 (2,163)	0.43*

Bonferroni correction was applied to the alpha level

* $p < .0001$ (two-tailed)

terms of profile differences rather than in severity differences alone. Overall, this point sits well with the fractionable autism triad hypothesis, which suggests a degree of independent etiology for the three DSM-IV symptom domains for Autistic disorder (Happé and Ronald 2008; Happé et al. 2006).

The results of the cluster analysis described here conflict with those of a comparable analysis employing the AQ in a high-functioning clinical sample ($n = 333$; aged 16 years and above, including adults; Ring et al. 2008). This prior study reports between two and four clusters distinguishable in terms of symptom severity but not in symptom profile. The discrepancy between studies could reflect a difference between the presentation of traits in clinical and nonclinical populations; however, it is important to appreciate that the former are *defined* by the co-occurrence of the diagnostic symptom domains, and thus Ring et al. (2008) address a question of how heterogeneity manifests when these symptoms co-occur, rather than how the relevant traits tend

to present in general. Other research that has examined the clustering of individuals within clinical ASD samples has typically focussed on children and employed measures other than the AQ. A recent latent class analysis of a large sample of nonclinical children, using questionnaire items based on DSM-IV diagnostic criteria, indicated four subgroups that differed not only in severity but also in symptom profile (Beuker et al. 2013). This latter finding is compatible with our results, although represents ASD-like characteristics at a significantly different stage of development.

The three-factor solution described in the present study indicates that the AQ is tapping into a ‘sociability’ construct, a ‘mentalising’ construct, and a ‘detail orientation’ construct. This finding closely matches those of two previous factor analyses of the AQ in smaller adult nonclinical samples (Austin 2005; Hurst et al. 2007). Other researchers, however, have reported 2, 4, or 5 factors (Stewart and Austin 2009; Hoekstra et al. 2008; Kloosterman et al. 2011;

Freeth et al. 2013b). The three-factor solution provides empirical support for three item subsets in the AQ: one subset resembling the existing Attention to Detail subscale, and two other subsets characterised, respectively, by ‘sociability’ and ‘mentalising’ items drawn from the three traditional social subscales. These results do not attest to the five subscales typically used in research, however, which include separate Social Skills, Communication, Imagination and Attention-Switching subscales.

It is worth reiterating that the Attention Switching subscale correlated positively with the three social-themed subscales, as well as with the Sociability and Mentalising factors identified empirically in the present study. This subscale consists of items such as “I prefer to do things the same way over and over again”, could be alternately labeled as ‘behavioural inflexibility’, and a priori would be considered a non-social feature of ASD. Similarly, there was no evidence from the factor analysis that the AQ items were tapping into a distinct ‘attention switching’ construct. Thus, findings based upon AQ scores (including the differences between clusters reported here) appear to be best explained in terms of social and detail-orientation characteristics. The positive association between Attention Switching items and social domains of the AQ may indicate that individual items in this subscale tap into social characteristics and share this in common to a greater degree than their tendency to tap into a unitary construct of attention switching. Another possibility is that attention switching is a trait (or set of traits) that benefits social behaviour.

The pattern of moderate-to-strong positive correlation between the Sociability and Mentalising factors, while the third Detail Orientation factor varied more independently, coheres reasonably well with the DSM-5 criteria for ASD, which encompass a social-communicative domain and a second, non-social domain (American Psychiatric Association 2013). A recent review of factor analytic studies employing clinical ASD samples similarly concludes that the most support exists for a two-factor solution consisting of distinct social and non-social domains (Shuster et al. 2013). The plurality of underlying constructs observed in the current and previous studies is consistent with the fractionable triad hypothesis, which suggests that the domains of ASD-like traits come apart to vary somewhat independently across the population. In the present study, a ‘detail orientation’ dimension stands out most distinctly from the rest of the AQ. Thus, the ‘fractionation’ in ASD-like traits in adults may occur most prominently between social (sociability and mentalising) and detail-orientation domains.

In terms of studying ASD via nonclinical samples, the present results indicate that adults tend to present with one of two differing combinations of traits. This implies that an

individual lower on total AQ might actually be higher in detail orientation (and hence, more similar to a clinical individual on this particular symptom set) than an individual higher in total AQ. Thus, it is preferable to examine cognitive and neurological measures of interest with respect to subsets of the questionnaire rather than to total AQ score. Our results demonstrate two main domains that present independently, to an extent, in the general population—social characteristics and detail orientation—indicating that individuals are best characterised with regard to their ASD-like presentation with the use of these two dimensions. Further to this point, the majority of items in the AQ assess social features of ASD, which may be important to note for studies examining cognitive or neurological functions in relation to composite AQ scores in nonclinical samples (with detail-orientation arising here as the primary non-social feature that the AQ assesses). The use of more specific, and empirically-supported, item subsets may enhance the likelihood of relating nonclinical findings to the heterogeneous clinical population.

A conceivable limitation of the present study is the use of an online sample, recruited via the Amazon Mechanical Turk system. The demographics of this population are well-described in several prior investigations, however, and it has been argued that samples recruited in this fashion are more representative of the general (US) population than tertiary student samples typically employed in psychological research (Paolacci et al. 2010; Berinsky et al. 2012; Buhrmester et al. 2011). In the present study, the average score on the AQ ($M = 20$, $SD = 6.9$) was higher than that reported previously for student nonclinical samples (e.g., $M = 17.6$, $SD = 6.4$; Baron-Cohen et al. 2001), but not drastically so, and not approaching that reported previously for clinical samples (e.g., $M = 35.8$, $SD = 6.5$; Baron-Cohen et al. 2001). The Amazon Mechanical Turk and other online recruitment systems are increasingly commonplace in scientific research (e.g., Kidd and Castano 2013; Quidbach et al. 2013). The use of online recruitment in the present experiment allowed for the analysis of a notably larger sample than that employed by almost all previous studies of ASD-like traits in adults.

To conclude, the present study provides a new perspective on the presentation of ASD-like traits in the adult population. Two distinct profiles were apparent following cluster analysis of a large general population sample, differing inversely in the magnitude of social and non-social (detail orientation) features of ASD. These differing profiles highlight a limitation in conceptualising ASD as a singular construct that varies across the population—and indicate, instead, that it is important to characterise adult individuals in their social- and detail-related traits independently. This coheres with the fractionable autism triad model better than a unitary spectrum view.

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Conflicts of interest The authors declare that they have no conflict of interest.

References

- American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders: DSM-IV-TR* (4th ed.). Washington, DC: American Psychiatric Association.
- American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders: DSM-5* (5th ed.). Arlington, VA: American Psychiatric Association.
- Austin, E. J. (2005). Personality correlates of the broader autism phenotype as assessed by the Autism Spectrum Quotient (AQ). *Personality and Individual Differences*, 38, 451–460.
- Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The autism-spectrum quotient (AQ): Evidence from Asperger syndrome/high-functioning autism, males and females, scientists and mathematicians. *Journal of Autism and Developmental Disorders*, 31(1), 5–17.
- Bayliss, A. P., & Tipper, S. P. (2005). Gaze and arrow cueing of attention reveals individual differences along the autism spectrum as a function of target context. *British Journal of Psychology*, 96(Pt 1), 95–114. doi:10.1348/000712604X15626.
- Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. *Political Analysis*, 20(3), 351–368.
- Beuker, K. T., Schjolberg, S., Lie, K. K., Donders, R., Lappenschaar, M., Swinkels, S. H., et al. (2013). The structure of autism spectrum disorder symptoms in the general population at 18 months. *Journal of Autism and Developmental Disorders*, 43(1), 45–56. doi:10.1007/s10803-012-1546-4.
- Bolton, P., Macdonald, H., Pickles, A., Rios, P., Goode, S., Crowson, M., et al. (1994). A case-control family history study of autism. *Journal of Child Psychology and Psychiatry*, 35(5), 877–900.
- Broadbent, J., Galic, I., & Stokes, M. A. (2013). Validation of autism spectrum quotient adult version in an Australian sample. *Autism Research and Treatment*, 2013, 1–7. doi:10.1155/2013/984205.
- Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, 6(1), 3–5.
- Chakrabarti, B., Dudbridge, F., Kent, L., Wheelwright, S., Hill-Cawthorne, G., Allison, C., et al. (2009). Genes related to sex steroids, neural growth, and social-emotional behavior are associated with autistic traits, empathy, and Asperger syndrome. *Autism Research*, 2(3), 157–177. doi:10.1002/aur.80.
- Chen, F. S., & Yoon, J. M. (2011). Brief report: broader autism phenotype predicts spontaneous reciprocity of direct gaze. *Journal of Autism and Developmental Disorders*, 41(8), 1131–1134. doi:10.1007/s10803-010-1136-2.
- Constantino, J. N., & Todd, R. D. (2003). Autistic traits in the general population: A twin study. *Archives of General Psychiatry*, 60(5), 524–530. doi:10.1001/archpsyc.60.5.524.
- Daunizeau, J., Adam, V., & Rigoux, L. (2014). VBA: A probabilistic treatment of nonlinear models for neurobiological and behavioural data. *PLoS Computational Biology*, 10(1), e1003441.
- Donohue, S. E., Darling, E. F., & Mitroff, S. R. (2012). Links between multisensory processing and autism. *Experimental Brain Research*, 222(4), 377–387. doi:10.1007/s00221-012-3223-4.
- Field, A. (2009). *Discovering statistics using SPSS* (3rd ed.). London: Sage.
- Freeth, M., Foulsham, T., & Kingstone, A. (2013a). What affects social attention? Social presence, eye contact and autistic traits. *PLoS ONE*, 8(1), e53286. doi:10.1371/journal.pone.0053286.
- Freeth, M., Sheppard, E., Ramachandran, R., & Milne, E. (2013b). A cross-cultural comparison of autistic traits in the UK, India and Malaysia. *Journal of Autism and Developmental Disorders*, 43(11), 2569–2583. doi:10.1007/s10803-013-1808-9.
- Grinter, E. J., Maybery, M. T., Van Beek, P. L., Pellicano, E., Badcock, J. C., & Badcock, D. R. (2009a). Global visual processing and self-rated autistic-like traits. *Journal of Autism and Developmental Disorders*, 39(9), 1278–1290. doi:10.1007/s10803-009-0740-5.
- Grinter, E. J., Van Beek, P. L., Maybery, M. T., & Badcock, D. R. (2009b). Brief report: Visuospatial analysis and self-rated autistic-like traits. *Journal of Autism and Developmental Disorders*, 39(4), 670–677. doi:10.1007/s10803-008-0658-3.
- Happé, F., & Ronald, A. (2008). The 'fractionable autism triad': A review of evidence from behavioural, genetic, cognitive and neural research. *Neuropsychology Review*, 18(4), 287–304. doi:10.1007/s11065-008-9076-8.
- Happé, F., Ronald, A., & Plomin, R. (2006). Time to give up on a single explanation for autism. *Nature Neuroscience*, 9(10), 1218–1220. doi:10.1038/nn1770.
- Hoekstra, R. A., Bartels, M., Cath, D. C., & Boomsma, D. I. (2008). Factor structure, reliability and criterion validity of the autism-spectrum quotient (AQ): A study in Dutch population and patient groups. *Journal of Autism and Developmental Disorders*, 38(8), 1555–1566. doi:10.1007/s10803-008-0538-x.
- Hurst, R. M., Mitchell, J. T., Kimbrel, N. A., Kwapil, T. K., & Nelson-Gray, R. O. (2007). Examination of the reliability and factor structure of the Autism Spectrum Quotient (AQ) in a non-clinical sample. *Personality and Individual Differences*, 43, 1938–1949.
- Jakab, A., Emri, M., Spisak, T., Szeman-Nagy, A., Beres, M., Kis, S. A., et al. (2013). Autistic traits in neurotypical adults: Correlates of graph theoretical functional network topology and white matter anisotropy patterns. *PLoS ONE*, 8(4), e60982. doi:10.1371/journal.pone.0060982.
- Kidd, D. C., & Castano, E. (2013). Reading literary fiction improves theory of mind. *Science*, 342(6156), 377–380. doi:10.1126/science.1239918.
- Kloosterman, P. H., Keefer, K. V., Kelley, E. A., Summerfeldt, L. J., & Parker, J. D. A. (2011). Evaluation of the factor structure of the autism-spectrum quotient. *Personality and Individual Differences*, 50, 310–314.
- Lai, M. C., Lombardo, M. V., Chakrabarti, B., & Baron-Cohen, S. (2013). Subgrouping the autism "spectrum": Reflections on DSM-5. *PLoS Biology*, 11(4), e1001544. doi:10.1371/journal.pbio.1001544.
- Lau, W. Y., Gau, S. S., Chiu, Y. N., Wu, Y. Y., Chou, W. J., Liu, S. K., et al. (2013a). Psychometric properties of the Chinese version of the Autism Spectrum Quotient (AQ). *Research in Developmental Disabilities*, 34(1), 294–305. doi:10.1016/j.ridd.2012.08.005.
- Lau, W. Y., Kelly, A. B., & Peterson, C. C. (2013b). Further evidence on the factorial structure of the Autism Spectrum Quotient (AQ) for adults with and without a clinical diagnosis of autism. *Journal of Autism and Developmental Disorders*, 43(12), 2807–2815. doi:10.1007/s10803-013-1827-6.
- Ledesma, R. D., & Valero-Mora, P. (2007). Determining the number of factors to retain in EFA: An easy-to-use computer program for carrying out parallel analysis. *Practical Assessment, Research & Evaluation*, 12(2), 1–11.

- Mandy, W. P., & Skuse, D. H. (2008). Research review: What is the association between the social-communication element of autism and repetitive interests, behaviours and activities? *Journal of Child Psychology and Psychiatry*, 49(8), 795–808. doi:10.1111/j.1469-7610.2008.01911.x.
- Martinez, W. L., Martinez, A. R., & Solka, J. L. (2011). *Exploratory data analysis with MATLAB. Chapman & Hall/CRC computer science and data analysis series (2nd ed.) pp. xix, 508 p., 508 p. of col.* Boca Raton, Fla: CRC Press.
- Murray, A. L., Booth, T., McKenzie, K., Kuenssberg, R., & O'Donnell, M. (2013). Are autistic traits measured equivalently in individuals with and without an Autism Spectrum Disorder? An invariance analysis of the Autism Spectrum Quotient Short Form. *Journal of Autism and Developmental Disorders*. doi:10.1007/s10803-013-1851-6.
- Nummenmaa, L., Engell, A. D., von dem Hagen, E., Henson, R. N., & Calder, A. J. (2012). Autism spectrum traits predict the neural response to eye gaze in typical individuals. *Neuroimage*, 59(4), 3356–3363. doi:10.1016/j.neuroimage.2011.10.075.
- O'Connor, B. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behavior Research Methods, Instruments, & Computers*, 32(3), 396–402.
- O'Connor, B. (2014). SPSS, SAS, and MATLAB programs for determining the number of components and factors. <https://people.ok.ubc.ca/briocconn/nfactors/nfactors.html>. Accessed 5 August 2014.
- Palmer, C. J., Paton, B., Hohwy, J., & Enticott, P. G. (2013). Movement under uncertainty: The effects of the rubber-hand illusion vary along the nonclinical autism spectrum. *Neuropsychologia*, 51(10), 1942–1951. doi:10.1016/j.neuropsychologia.2013.06.020.
- Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on Amazon Mechanical Turk. *Judgment and Decision Making*, 5(5), 411–419.
- Piven, J., Palmer, P., Jacobi, D., Childress, D., & Arndt, S. (1997). Broader autism phenotype: Evidence from a family history study of multiple-incidence autism families. *American Journal of Psychiatry*, 154(2), 185–190.
- Posserud, M. B., Lundervold, A. J., & Gillberg, C. (2006). Autistic features in a total population of 7-9-year-old children assessed by the ASSQ (Autism Spectrum Screening Questionnaire). *Journal of Child Psychology and Psychiatry*, 47(2), 167–175. doi:10.1111/j.1469-7610.2005.01462.x.
- Puzzo, I., Cooper, N. R., Vetter, P., & Russo, R. (2010). EEG activation differences in the pre-motor cortex and supplementary motor area between normal individuals with high and low traits of autism. *Brain Research*, 1342, 104–110. doi:10.1016/j.brainres.2010.04.060.
- Quoidbach, J., Gilbert, D. T., & Wilson, T. D. (2013). The end of history illusion. *Science*, 339(6115), 96–98. doi:10.1126/science.1229294.
- Ring, H., Woodbury-Smith, M., Watson, P., Wheelwright, S., & Baron-Cohen, S. (2008). Clinical heterogeneity among people with high functioning autism spectrum conditions: Evidence favouring a continuous severity gradient. *Behavioral and Brain Functions*, 4, 11. doi:10.1186/1744-9081-4-11.
- Robinson, E. B., Koenen, K. C., McCormick, M. C., Munir, K., Hallett, V., Happé, F., et al. (2011). Evidence that autistic traits show the same etiology in the general population and at the quantitative extremes (5 %, 2.5 %, and 1 %). *Archives of General Psychiatry*, 68(11), 1113–1121. doi:10.1001/archgenpsychiatry.2011.119.
- Robinson, E. B., Koenen, K. C., McCormick, M. C., Munir, K., Hallett, V., Happé, F., et al. (2012). A multivariate twin study of autistic traits in 12-year-olds: Testing the fractionable autism triad hypothesis. *Behavior Genetics*, 42(2), 245–255. doi:10.1007/s10519-011-9500-3.
- Ronald, A., Happé, F., Bolton, P., Butcher, L. M., Price, T. S., Wheelwright, S., et al. (2006a). Genetic heterogeneity between the three components of the autism spectrum: A twin study. *Journal of the American Academy of Child and Adolescent Psychiatry*, 45(6), 691–699. doi:10.1097/01.chi.0000215325.13058.9d.
- Ronald, A., Happé, F., & Plomin, R. (2005). The genetic relationship between individual differences in social and nonsocial behaviours characteristic of autism. *Developmental Science*, 8(5), 444–458. doi:10.1111/j.1467-7687.2005.00433.x.
- Ronald, A., Happé, F., & Plomin, R. (2006b). Genetic research into autism. *Science*, 311(5763), 952; (author reply) 952, doi:10.1126/science.311.5763.952a.
- Ronald, A., Larsson, H., Anckarsater, H., & Lichtenstein, P. (2011). A twin study of autism symptoms in Sweden. *Molecular Psychiatry*, 16(10), 1039–1047. doi:10.1038/mp.2010.82.
- Shuster, J., Perry, A., Bebko, J., & Toplak, M. E. (2013). Review of factor analytic studies examining symptoms of Autism Spectrum Disorders. *Journal of Autism and Developmental Disorders*. doi:10.1007/s10803-013-1854-3.
- Stevens, J. (2009). *Applied multivariate statistics for the social sciences* (5th ed.). New York: Routledge.
- Stewart, M. E., & Austin, E. J. (2009). The structure of the autism-spectrum quotient (AQ): Evidence from a student sample in Scotland. *Personality and Individual Differences*, 47, 224–228.
- Sutherland, A., & Crewther, D. P. (2010). Magnocellular visual evoked potential delay with high autism spectrum quotient yields a neural mechanism for altered perception. *Brain*, 133(Pt 7), 2089–2097. doi:10.1093/brain/awq122.
- Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B*, 63(2), 411–423.
- van Boxtel, J. J., & Lu, H. (2013). Impaired global, and compensatory local, biological motion processing in people with high levels of autistic traits. *Frontiers in Psychology*, 4, 209. doi:10.3389/fpsyg.2013.00209.
- Walter, E., Dassonville, P., & Bochsler, T. M. (2009). A specific autistic trait that modulates visuospatial illusion susceptibility. *Journal of Autism and Developmental Disorders*, 39(2), 339–349. doi:10.1007/s10803-008-0630-2.
- World Health Organization. (2004). *ICD-10: International statistical classification of diseases and related health problems 10th revision* (2nd ed.). Geneva: World Health Organization.