Identifying and Describing Subtypes of Spontaneous Empathic Facial Expression Production in Autistic Adults

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RESEARCH

Identifying and Describing Subtypes of Spontaneous Empathic Facial Expression Production in Autistic Adults

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Abstract

Background: It is unclear whether atypical patterns of facial expression production metrics in autism reflect the dynamic and nuanced nature of facial expressions or a true diagnostic difference. Further, the heterogeneity observed across autism symptomatology suggests a need for more adaptive and personalized social skills programs. For example, it would be useful to have a better understanding of the different expressiveness profiles within the autistic population and how they differ from neurotypicals to help develop systems that train facial expression production and reception.

Methods: We used automated facial coding and an unsupervised clustering approach to limit inter-individual variability in facial expression production that may have otherwise obscured group differences in previous studies, allowing an "apples-to-apples" comparison between autistic and neurotypical adults. Specifically, we applied k-means clustering to identify subtypes of facial expressiveness in an autism group (N=27) and a neurotypical control group (57) separately. The two most stable clusters from these analyses were then further characterized and compared on the basis of their expressiveness and emotive congruence to emotionally charged stimuli.

Results: Our main finding was that autistic adults show heightened spontaneous facial expressions in response to negative emotional images. The group effect did not extend to positive emotional images, and we did not find evidence for greater incongruous (i.e., inappropriate) facial expressions in autism.

Conclusion: These findings build on previous work suggesting valence-specific effects of autism on emotional empathy and suggest the need for intervention programs to focus on social skills in the context of both negative and positive emotions.

Keywords: autism spectrum disorder; facial expression production; empathy; non-verbal communication

Background

Autism Spectrum Disorder (ASD; henceforth also referred to as "autism") is a neurodevelopmental condition exemplified by difficulties with socio-emotional communication skills, and engaging in restricted, repetitive patterns of behavior, interests, and activities [1]. Within the socio-emotional domain, the capacity to understand and use nonverbal communication is thought to be central to developing and maintaining healthy social relationships throughout the lifespan [2], as well as facilitate learning and workforce outcomes [3]. Persistent social difficulties translate to difficulties developing and maintaining social relationships throughout adulthood and are associated with depression, anxiety, loneliness and isolation [4]. Given the pervasiveness and impact of socio-emotional difficulties in autism, many social skills intervention programs are designed to facilitate training in socially-relevant nonverbal cue usage, production, and understanding by means of in-person and technology-based paradigms [5].

In-person social skills intervention programs provide structured opportunities to learn and practice social skills and have been shown to improve social metrics like friendship quality, social functioning, and reducing feelings of loneliness in youth and adult autistic groups [6, 7]. Group-based interventions are among the most widely used approaches and yield substantial benefits in self-reported social knowledge, but these gains do not reliably translate to objective laboratory-based measures, or, more importantly, parent/teacher reports [6]. In addition to these limitations, in-person training programs are resource-intensive for both healthcare systems and families, requiring extensive clinical training, administration and family transportation services. Access to these resources is especially limited given a scarcity of available autism service providers [8] and has been exacerbated by recent COVID-19 related restrictions.

Emerging automated technology systems supported by machine learning have facilitated the administration and improved the accessibility of autism services like social skills interventions [9]. Supervised and unsupervised machine learning approaches hold promise for predicting outcomes and identifying subgroups based on symptom profiles [10]. Current applications for computational methods in autism research include diagnostic methods [11], the analysis of facial expressions production [12, 13], behavioral and physiological signals [14]. Facial expression production and reciprocity are, in particular, central to important socio-emotional constructs like emotional regulation [15] and the success of social interactions [16]. Within the autistic population, facial expressions are found to be atypical in appearance metrics like social congruence, frequency, or duration [17]. In practice, these differences may lead to negative evaluations from peers and reduce the overall quality of social interactions [18]. Interestingly, previous reports do not suggest that facial expression intensity is affected in autism [19], despite prevalent clinical descriptions of both "flat affect" [20, 21] and "exaggerated" expressions [22, 23]. It is possible however, that in group comparison studies, distinct subgroups of extreme high and low levels of expressivity average one another out and mask differences that are not uniform in direction within the autistic population. Computational approaches such as k-means clustering can help to differentiate this scenario from a true lack of group difference in facial expression intensity.

The heterogeneity observed across autism symptomatology suggests a need for more adaptive and personalized social skill interventions programs. For example, it would be useful to have a better understanding of the different expressiveness profiles within the autistic population and how they differ from neurotypicals (NT) before deploying systems to help train facial expression production and reception. To this end, we cluster autistic and neurotypical adults separately on the basis of their facial expressions within the socially relevant context of empathy. Empathy has long been considered a sub-domain of the social communication difficulties present in autism [24], but more current evidence suggests a much more nuanced picture [25] given the multi-faceted nature of empathy measurement. Relevant domains span psychophysiology, social cognition, and affective response, with the literature dominated by top-down paradigms that do not address the inherent reciprocity in dyadic interactions [26, 27, 28]. Thus, our goal was to gain deeper inferential insights on profiles of expressiveness and features of autism across these separate but related domains.

Methods

Our primary objective for this paper was to explore whether the atypical patterns of facial expression production metrics in autism reflect the dynamic and nuanced nature of facial expressions or a true diagnostic difference. To this end, we collected facial videos during an experimental study, derived a set of automated facial expression features from the videos using the iMotions affect recognition toolkit [29, 30], and applied an exploratory unsupervised learning approach on the feature sets for ASD and NT participants separately to derive interpretable clusters.

Participants

A total of 84 participants, originally part of a larger study, were included in this analysis. The current sample ($n = 84$) consisted of 27 ASD participants (12 female, 14 male, 1 other) and 57 neurotypical (NT) participants (21 female, 36 male). All participants in this sample were adults between the ages of 18 & 59 years. Participants were pre-screened using the Wechsler Abbreviated Scale of Intelligence Second Edition (WASI-II) [31], with Full Scale IQ (FSIQ) scores ≥ 70. Participants also completed the Social Responsiveness Scale-2 (SRS-2), a self-report questionnaire that measures autistic traits [32].

Autism diagnoses for participants were confirmed by the clinical judgment of a licensed psychologist specializing in the assessment of ASD, supported by research-reliable administration of the Autism Diagnostic Observation Schedule-2 (ADOS-2) [33]. Exclusion criteria for both ASD and NT groups included the presence of other neurological and genetic disorders, non-ASD related sensory impairments (e.g., uncorrected visual or hearing impairments), and substance/alcohol abuse or dependence during the past two years. Further, individuals in the NT group were excluded if they had reported a previous psychiatric history, cognitive or sensory impairment, use of psychotropic medications, or clinically elevated scores on the Social Communication Questionnaire ([34]). Individuals with ASD and co-occurring ADHD, anxiety, or depression were included, while those with other recent psychiatric diagnoses within the past five years or co-occurring neurogenetic syndromes were excluded. Participants were compensated $20 per hour of their time following each session. All procedures were approved by the Institutional Review Board for human subjects at Vanderbilt University Medical Center.

Experimental Procedure

We captured participants' facial expressions while they completed an adapted version of the Multifaceted Empathy Test (MET) [35], a validated multidimensional computer-based task that separates arousal, emotional, and cognitive components of empathy. A full description of the MET can be found in Quinde-Zlibut et al. [25]; briefly, the adapted version presently used includes 32 emotionally charged photographs depicting positive and negative scenarios and is known as the MET-J [36].

In the present study, the task was designed to be compatible with the iMotions v.6 computer software platform for biosensor integration [29]. The facial expressions of interest for the cluster analysis were recordings from trials where participants viewed an emotional image (either positive or negative valence) and were asked to answer: *"While looking at the picture, how much do your feelings match the boy's feelings?"*. Note that while the previous example is for a photograph of a boy, the task included standardized and validated images of males and females of all ages [37].

Data Collection

Participants in the MET study worked individually on webcam-enabled laptops, which facilitated the collection of facial videos. The videos were processed *post hoc* using the iMotions AffDex SDK. AffDex detected facial landmarks from the video frames, extracted features and used Ekman & Friesen's Emotional Facial Action Coding System (EMFACS) [38] to accurately classify 'facial action units' (AUs) [30]. A combination of these facial AUs was then used by AffDex to compute likelihood values for a set of facial expression metrics like, *facial engagement/expressiveness* and *emotional valence*. These values, derived by AffDex from the video frames at a frequency of 30Hz, are further defined as below:

1 *Engagement/Expressiveness:* A general measure of overall facial expressiveness, computed as the average of the highest evidence scores from upper *(Brow raise, Brow furrow, Nose wrinkle)* and lower face region *(Lip corner depressor, Chin raise, Lip pucker, Lip press, Mouth open, Lip suck, Smile)*, respectively.
2 *Valence:* A measure of the affective quality of the facial expression, i.e., how positive or negative the associated emotion is. Increased positive valence was determined in AffDex by high likelihood of AUs like *Smile and Cheek Raise*, while increased negative valence was determined by high likelihood of AUs like *Inner Brow Raise, Brow Furrow, Nose Wrinkle, Upper Lip Raise, Lip Corner Depressor, Chin Raise, Lip Press and Lip Suck.*

Approach for Clustering the ASD & NT groups

Feature Selection

For each group (NT & ASD), we constructed a set of four features from the data processed through iMotions. The features, listed below, reflect overall levels of facial expressiveness and emotional valence of participants under two different experimental conditions: *(a) When they responded to images evoking positive emotion valence*, and *(b) When they responded to images evoking negative emotion valence.* For each participant, we computed the average peak expressiveness and valence scores across trials depicting images of positive and negative emotional valence.

1 Expressiveness (−): Average peak expressiveness score for images with negative valence.
2 Expressiveness (+): Average peak expressiveness score for images with positive valence.
3 Valence (−): Average peak emotion valence score for images with negative valence.

4 Valence (+): Average peak emotion valence score for images with positive valence.

The *coefficient of variation* ($\frac{SD}{Mean}$) was computed for each constructed feature, as a variance-based feature selection criterion. All four features had coefficients of variation $> 20\%$, and were included for clustering. Further, to avoid any potential order-of-magnitude related feature biases, each feature was Z-score standardized.

K-Means Clustering

A K-means algorithm was applied on the processed feature set of each group (ASD & NT) using the k-means implementation available in the *cluster* package [39] in the R environment for statistical computing [40]. K-means is a distance-based algorithm that clusters data points based on how similar they are to one another. Similarity is defined as the Euclidean distance between points such that the lower the distance between the points, the more similar they are. Likewise, the greater the distance, the more dissimilar they are [41]. In practice, the K-means algorithm clusters data points using the following steps:

1 *Choice of an optimal value for k clusters:* For the present analysis we used the total within sum of squares (WSS) method. This involves comparing how the WSS changes with increasing number of clusters and identifying the number of clusters associated with the biggest drop in WSS. In our case, the optimal number of clusters determined by this method was $k = 2$ for both the ASD and NT cluster analyses.
2 *Random assignment of each data point to an initial cluster from 1 to K:* This step involves matching each participant with the closest centroid in an n-dimensional space where n corresponds to the number of features (in this case $n = 4$).
3 *Centroid Recalculation:* After participants are assigned to k clusters, the centroids are recalculated as the mean point of all other points in the group.
4 *Cluster Stabilization:* Steps 2 and 3 are repeated until participants are no longer reallocated to another centroid.

The resulting clusters were validated and assessed based on their *average silhouette widths*, a measure of how similar each data point is to its own cluster compared to other clusters. Positive silhouette (Si) values indicate appropriately clustered data (the closer to 1, the better the data was assigned). Negative Si values indicates inappropriately clustered data while Si values of 0 indicate that the data point falls between two clusters.

ASD and NT Group Comparison

For the purpose of determining whether there is a true difference in facial expressiveness, we conducted ASD-NT group comparisons on the stable sub-types identified from the separate ASD and NT cluster analyses. We computed a robust, non-parametric effect-size statistic, Cliff's delta [42, 43] using the *orddom* package [44] in R. Delta does not require any assumptions regarding the shape or spread of two distributions and estimates the probability that a randomly selected observation from one distribution is larger than a randomly selected observation from another distribution, minus the reverse probability. Possible delta (δ) values range from -1

to 1, where values of 0 indicate a complete overlap of groups and values of −1 or 1 indicate that all the values in one group are larger than all the values in the other.

Our variables of interest for this analysis included age, average peak engagement/expressiveness, average emotion congruence, average expressiveness scores specific to negative images, average expressiveness scores specific to positive images, and all the SRS-2 subscales. Average expressiveness was calculated as an average of the expressiveness scores to both negative and positive images. Average congruence was calculated as the average number of instances when a participant's valence scores matched the emotional valence of the MET images (i.e. when the valence score was greater than 0 and the image was positive, the facial expression was marked as congruent).

Results

K-means clustering

ASD Cluster analysis

The k-means model identified two clusters (Fig 1a) within our ASD sample (N = 27):

1. Cluster 1 (n=19) with an average Si of 0.56
2. Cluster 2 (n=8) with an average Si of 0.14

Further characterization of the two ASD subgroups can be found in Figure 2a. Subgroup comparisons revealed that Cluster 1 differed from Cluster 2 in average engagement/expressiveness ($\delta = 0.934, p < .001$), and average congruence ($\delta = -0.434, p = 0.035$). Cluster 2 was therefore characterized as a more exaggerated group whose facial expressions were not always congruent with the stimulus' emotional valence.

NT Cluster analysis

The k-means algorithm identified two clusters (Fig 1b) within our NT sample (N=57):

1. Cluster 1 (n=39) with an average Si of 0.55
2. Cluster 2 (n=18) with an average Si of 0.20

Further characterization of the two NT groups can be found in Figure 2b. Subgroup comparisons revealed that Cluster 1 differed from Cluster 2 in average engagement/expressiveness ($\delta = 0.940, p < .001$), and average congruence ($\delta = -0.625, p < .001$). Cluster 2 was therefore also characterized as a more exaggerated group whose facial expressions were not always congruent with the stimulus' emotional valence.

Comparison of the Stable ASD and NT Clusters

After identifying the two more stable subgroups within our ASD and NT samples, we compared them to identify whether these differed in facial expressiveness and social symptomatology metrics. We found that the two groups did not differ in either of our facial expression metrics, average expressiveness ($\delta = -0.314, p = .068$), or average congruence ($\delta = 0.288, p = 0.091$). When considering facial expressiveness to positive and images separately, we found that the ASD group was significantly more expressive in response to negative images than our NT group ($\delta = -0.009, p = 0.032$; Fig 3). Lastly, the two groups were significantly different in all SRS-2 subscales (Table 1).

Discussion

In this study, a primary goal was to use computational approaches to address discrepancies in the literature on spontaneous empathic facial expressions in autistic adults. Facial expression as a means of registration and communication of emotion is a highly nuanced behavioral phenomenon characterized by high inter-individual variability [45] and strong developmental effects [46]. The literature is further complicated by the use of a variety of research methods, with drastic differences in the method of eliciting facial expressions (ranging from explicitly asking participants to produce a facial expression to eliciting spontaneous expressions with a nonsocial (e.g., a foul odor) or a social (e.g., another face making an expression) stimulus). Studies also differ in the method of measuring facial expressions (ranging from coding by observers who may or may not have formal training in facial coding [38], to electromyography of facial muscles, or automated algorithms for coding facial action). Thus, methodological and individual variability has presented a challenge to a clear understanding of how facial expression production differs in autism. A recent meta-analysis [17] found that, across various approaches, autistic people on average appear to differ on the quality and frequency of facial expressions, but are largely similar to neurotypicals in the intensity and timing of facial expressions. However, given that the studies in this analyses included a range of the aforementioned variations and noted moderating effects of individual factors, there is still a considerable lack of clarity on the effect of autism on spontaneous empathic facial expressions specifically, which are more likely to relate to empathy than elicited/requested expressions or spontaneous expressions to non-social stimuli.

For this reason, we focused on spontaneous facial expressions to images depicting an emotional face–a variant of facial mimicry. We restricted our sample to adults and used automated facial coding to capture participants' spontaneous facial expressions when viewing images of other people in emotionally charged situations. These data were then subjected to clustering analyses to isolate reliable subgroups based on overall levels of facial expressiveness or engagement. We found that both autistic and non-autistic adults could be separated into two clusters: a larger cluster with relatively lower overall intensity and more within-cluster homogeneity in the intensity of spontaneous facial expressions, and a smaller cluster that exhibited higher intensity overall but with significant variability between individuals in the cluster.

In order to limit the potential for inter-individual variability in this nuanced behavior to obscure meaningful differences, we used only the larger and more stable cluster in each group for subsequent group analyses. Our primary finding was that, among this subset, the autistic group showed higher facial engagement relative to the neurotypical group in response to negative emotional images. The two groups did not differ on engagement to positive images, nor on congruency (the extent to which the participant's facial expression matched that in the image) for either positive or negative images. This suggests that a greater proportion of the more limited engagement in the more stable cluster was toward negative images in the autistic adults. This is consistent with previous findings of higher intensity facial expressions driven by negative emotions [22] and may reflect a negative bias in interpreting facial expressions reported in autistic adults, in which happy faces tend to be construed as neutral, while neutral faces as having a negative valence [47]. Earlier work drawing on parent report also noted heightened expressiveness in negative emotional contexts in autism [48]. This result is also consistent with our recent findings on self-reported emotional empathy, or the feeling of emotional resonance, in autism. We reported that, while neurotypicals self-report higher emotional resonance to positive than negative images, for autistic people, resonance to negative images is similar to that for positive, making it relatively higher in comparison [25]. Finally, this finding adds to and extends the findings of intact facial mimicry in autism [49]. The meta-analysis by Trevisan and colleagues (2018), corroborated no average group differences in the intensity of facial expression production, but did not examine studies separately by emotional valence. Our findings support a lack of average differences in intensity, while highlighting a difference that depends on the valence of the stimuli.

The presence of subgroups and group differences based on intensity of facial expressions in both the neurotypical and autistic samples without accompanying differences in the congruence or appropriateness of facial expressions suggests a possible role for individual differences in the affective and sensorimotor aspects of facial expression production. Motor programs to produce an automatic facial expression in response to an emotional image may be initiated as expected, suggesting intact feedforward input from amygdala to facial motor circuitry [50]. However, in autistic adults, the end result of executing this program is an exaggerated facial expression specific to negative stimuli, which could reflect altered use of sensory feedback from facial skin and muscle to both facial motor and affective brain regions.

Our finding of equivalent congruency in the more stable clusters suggests does not preclude a subset of individuals characterized by inappropriate or incongruent facial expressions, as is commonly described clinically in a minority of people on the spectrum. Indeed, the smaller and less stable clusters in our sample, which were too small for us to further probe for group differences, may represent this subset of the autistic population. A limitation of this study is the small sample size that prevented us from further defining this subgroup. Other limitations of the study include the use of static stimuli rather than dynamic or interactive social stimuli, thus future work should consider alternative paradigms that more closely align with real-world social situations that elicit spontaneous facial expressions. Future studies should also examine this phenomenon in child and/or adolescent samples and individuals with co-occurring intellectual disability to better understand the influence of development and cognitive ability.

Conclusion

In this study, our main finding was that autistic adults show heightened spontaneous facial expressions in response to negative emotional images. We used automated facial coding and a clustering approach to limit inter-individual variability that may have otherwise obscured group differences in previous studies, allowing an "apples-to-apples" comparison between autistic and neurotypical adults. The group effect did not extend to positive emotional images, and we did not find evidence for greater incongruous (i.e., inappropriate) facial expressions in autism. These findings build on previous work suggesting valence-specific effects of autism on emotional empathy and suggest the need for intervention programs to focus on social skills in the context of both negative and positive emotions.

Figures

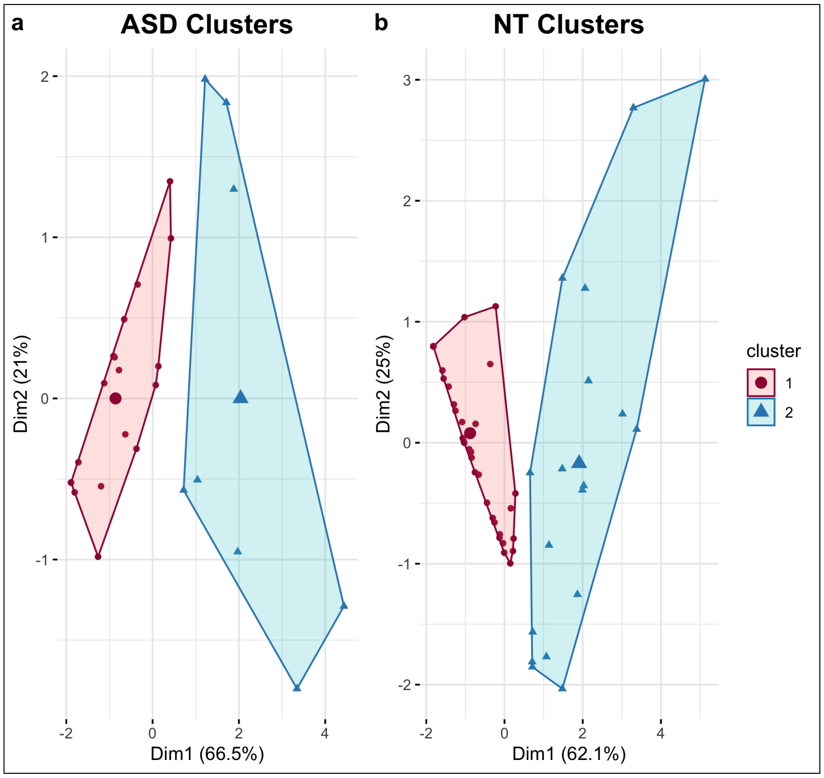

Figure 1 Clusters found in (a) ASD (N=27) and (b) NT Adults (N=57). The ASD cluster analysis revealed a larger more stable cluster (Cluster 1, n = 19) and a smaller, more unstable cluster (Cluster 2, n=8). The NT cluster analysis revealed a larger more stable cluster (Cluster 1, n=39) and a smaller, more unstable cluster (Cluster 2, n=18).

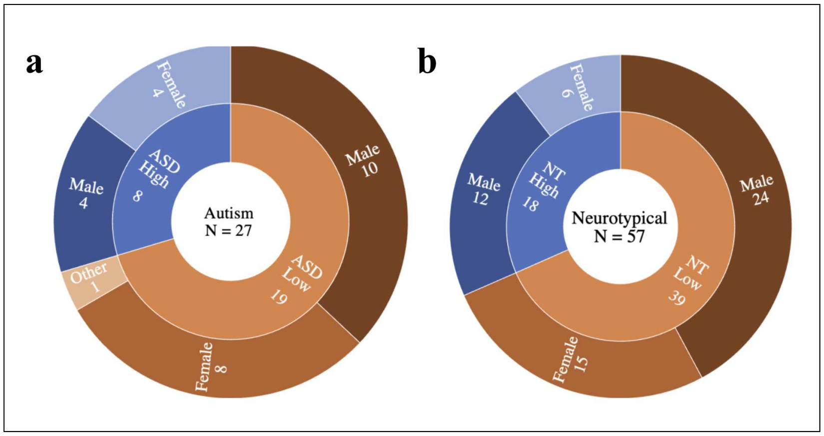

Figure 2 Number of (a) ASD (n=27) and (b) NT Adults (n=57) in each cluster grouped by engagement *(High, Low)* and gender *(Male, Female)*.

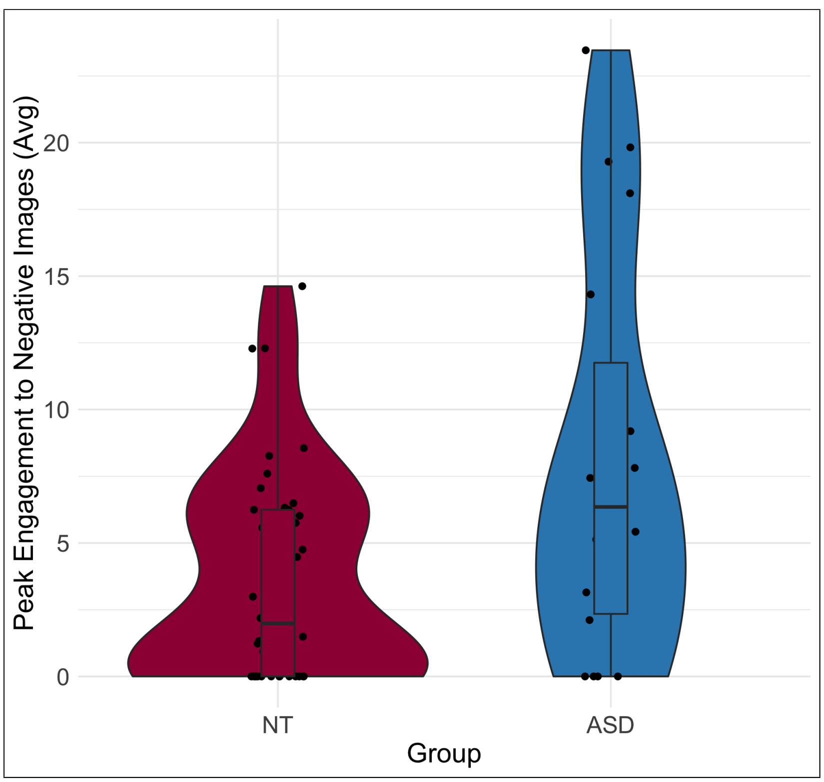

Figure 3 Average peak engagement/expressiveness to negative images in NT and ASD Adults ($\delta = -0.009, p = 0.032$).

Tables

Table 1 Aggregated statistics on facial expressiveness, emotion congruency and social responsiveness survey (SRS-2) scores for the two stable clusters (ASD:Cluster1 & NT:Cluster1) across ASD & NT groups.

Variable	ASD: Cluster 1 (n=19)		NT: Cluster 1 (n=39)		δ (95% CI)	p.value
	Mean	SD	Mean	SD		
Age (years)	28.34	9.75	31.15	7.68	0.31 (-0.06, 0.599)	0.08
Engagement / Expressiveness						
Average expressiveness	7.75	7.56	3.69	3.69	-0.31 (-0.31,-0.6)	0.068
Expressiveness ($-$)	7.95	7.5	3.63	4.03	-0.35 (-0.35,-0.61)	**0.03**
Expressiveness ($+$)	7.56	8.5	3.74	4.8	-0.23 (-0.23 , -0.53)	0.17
Average congruence	97.99	2.53	99.1	1.64	0.29 (0.29,-0.06)	0.09
SRS-2						
Social Awareness T-score	60.95	10.42	45.68	7.86	-0.75 (-0.75, -0.89)	**0**
Social Cognition T-score	64.05	10.51	45.54	7.76	-0.85 (-0.85, -0.94)	**0**
Social Communication T-score	66.47	11.34	46.76	8.01	-0.81 (-0.81 , -0.94)	**0**
Social Motivation T-score	66.95	11.4	50.73	9.13	-0.71 (-0.71, -0.87)	**0**
Restricted Interests & Repetitive Behaviour T-score	72.95	12.36	46.11	6.04	-0.94 (-0.94, -0.98)	**0**

p.values in **bold** *indicate statistically significant differences between the clusters.*

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Abbreviations
ASD: Autism Spectrum Disorder, NT: Neurotypical, COVID: Coronavirus disease, WASI: Wechsler Abbreviated Scale of Intelligence, ADOS: Autism Diagnostic Observation Schedule, ADHD: Attention Deficit Hyperactivity Disorder, MET: Multifaceted Empathy Task, EMFACS: Emotional Facial Action Coding System, AU: Action Units, SD: Standard Deviation, WSS: Within Sum of Squares, SRS: Social Responsiveness Scale

Availability of data and materials
The dataset used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate
Written informed consent forms were signed by all participants. Participants were compensated $20 per hour of their time following each session. All procedures were approved by the Institutional Review Board for human subjects at Vanderbilt University Medical Center.

Competing interests
The authors declare that they have no competing interests.

Consent for publication
Not applicable

Authors' contributions
JMQZ and CC conceptualized the study. JMQZ and AM performed background reading, data cleaning and management, and statistical analysis. JMQZ, CJC, and AM wrote the main manuscript text. CJC and GB oversaw the statistical analysis and manuscript preparation.

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