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Article *in* Journal of Autism and Developmental Disorders · October 2018

DOI: 10.1007/s10803-018-3625-7

Journal of Autism and Developmental Disorders
https://doi.org/10.1007/s10803-018-3625-7

ORIGINAL PAPER

Statistical Learning is Associated with Autism Symptoms and Verbal Abilities in Young Children with Autism

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Abstract

Statistical learning-extracting regularities in the environment-may underlie complex social behavior. 124 children, 56 with autism and 68 typically developing, ages 2–8 years, completed a novel visual statistical learning task on an iPad. Averaged together, children with autism demonstrated less learning on the task compared to typically developing children. However, multivariate classification analyses characterized individual behavior patterns, and demonstrated a subset of children with autism had similar learning patterns to typically developing children and that subset of children had less severe autism symptoms. Therefore, statistically averaging data resulted in missing critical heterogeneity. Variability in statistical learning may help to understand differences in autism symptoms across individuals and could be used to tailor and inform treatment decisions.

Keywords Statistical learning · Autism · Social communication · Cognitive abilities · Bayes classification

Introduction

Statistical learning is the fundamental ability to extract regularities in the environment over time without conscious awareness or the intention to learn (Perruchet and Pacton 2006; Saffran et al. 1996; Schapiro and Turk-Browne 2015). It has been proposed that statistical learning is the foundation for successful social interactions and social behavior (Meltzoff et al. 2009; Reeb-Sutherland et al. 2012; Wu et al. 2011). Individuals with Autism Spectrum Disorder (ASD) have impairments in social communication with significant heterogeneity in severity of social and language symptoms (Fountain et al. 2012; Lord and Jones 2012; Pickles et al. 2014). Researchers and clinicians have suggested that ASD symptoms may be related to a general deficit in picking up regularities in one's environment (Kavale and Forness 1996; Kuhl et al. 2005), but little work has directly tested this hypothesis in young children with ASD (although see Klinger et al. (2007)). In ASD, statistical learning studies have focused on older children and adults as well as examining learning abilities comparing groups of children (autism vs. typical development). Thus, there is little information in children below 7 years of age. Furthermore, there is little research assessing heterogeneity in learning abilities in children with ASD. The present study targeted younger children (2 years of age and older), with the goal of developing tools that would quantify learning abilities in individual participants and to test if visual statistical learning was related to severity of ASD symptoms and other core diagnostic features.

Prior work has shown varied results as to whether children, adolescents and adults with ASD demonstrate impairments in statistical learning. Some studies found deficits in motor and visual statistical learning in ASD (Gidley Larson and Mostofsky 2008; Gordon and Stark 2007) while others suggest no impairments in auditory or visual statistical learning (Barnes et al. 2008; Brown et al. 2010; Mayo and Eigsti 2012; Nemeth et al. 2010) and or even enhancement (Roser et al. 2015). Of note, two recent meta-analyses summarized

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10803-018-3625-7) contains supplementary material, which is available to authorized users.

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Published online: 31 May 2018

the auditory and motor statistical learning literature in ASD and suggested no impairments in individuals with ASD compared to typically developing (TD) individuals (Foti et al. 2015; Obeid et al. 2016). While it is possible that discrepancies in the literature were due to methodological differences across tasks, it is also likely that there was significant variability in statistical learning across individuals with ASD. Thus the inconsistencies across studies could be based upon differences in the children who participated. In all of these studies, analyses averaged groups of individuals with ASD and compared them to averages of TD individuals, eliminating the possibility of studying heterogeneity in ASD. A goal of the present study was to not only use univariate statistics to compare diagnostic groups, but utilize multivariate methods that would allow for classifiying of individuals based upon their patterns of learning (Tarpey et al. 2016). Bayes probability classification can quantify each child's behavior and assess how similar or dissimilar his/her behavior is to other children. Thus these methods can classify how well a child learns the task.

With the exception of (Gordon and Stark 2007; Jeste et al. 2015), previous statistical learning tasks have focused on children with ASD ages 7 and older. Thus we have limited understanding of whether there are general learning impairments in younger children with ASD. There is accumulating evidence that earlier behavioral interventions are associated with improved outcomes (Estes et al. 2015; MacDonald et al. 2014), with the majority of behavioral interventions for children with ASD built upon basic learning principles (Dawson et al. 2010). Thus more information about how younger children with ASD, below the age of 7, learn regularities in the environment, as well as identification of variability across very young children could be critical for improving and potentially tailoring early interventions for specific children. Further, we know little about how a range of cognitive abilities impact statistical learning as the majority of previous work has focused on individuals with normal or above average verbal and non-verbal IQs. Demonstrating similarities or differences in statistical learning in young children with ASD with high and low IQs is important for understanding why early interventions may be more effective in certain children.

Previous literature suggests a relationship between statistical learning and higher order skills such as language and adaptive skills. Individual variation in statistical learning in the auditory domain has been related to literacy (Arciuli and Simpson 2012) and vocabulary development (Shafto et al. 2012). Individuals with ASD who demonstrated clearer visual statistical learning through EEG signal variations had higher non-verbal IQs and increased adaptive social functioning (Jeste et al. 2015). Similarly, increased fMRI signals relating to auditory learning was associated with less severe social communication symptoms (Scott-Van Zeeland et al. 2010). To date, research demonstrating associations between ASD symptoms, cognitive skills and statistical learning used neural signals as the measures of statistical learning, rather than a behavioral output such as reaction times. Our goal was to create a visual task that yielded a replicable behavioral measurement to test whether individual differences in statistical learning as measured by reaction times would relate to core autism symptoms and verbal and non-verbal IQ. We chose to focus on the visual domain to map directly onto behavioral interventions that focus on non-verbal social communication skills (gestures, gaze) with face-to-face interactions.

The present study used a novel task of statistical learning on an iPad that could be completed by young children with ASD with a range of cognitive abilities and TD children. We utilized univariate statistics to test whether there were differences in implicit learning in young children with ASD versus TD. Multivariate classification analyses, specifically Bayes probabilities, tested the extent to which children with ASD demonstrated patterns of learning similar to TD children. We tested the classification results for associations with autism symptoms and cognitive abilities. We predicted that comparing the two groups would demonstrate that children with ASD have more difficulties with statistical learning compared to TD children. Second, we predicted overlap between a subset of children with ASD and TD children. Lastly, we hypothesized that enhanced learning abilities would be associated with less severe social communication symptoms in ASD and higher cognitive scores in both children with ASD and TD children.

Methods

Participants

We recruited 130 children (ages 2–8, mean age = 5.2, SD = 1.3) to participate in the study through the Center for Autism and the Developing Brain (CADB) and the Sackler Institute for Developmental Psychobiology. Caregivers provided informed consent and children 7 years of age and older provided assent. The study was approved by the Weill Cornell Medicine IRB.

73 typically developing children were screened by caregiver report for ASD with the Social Communication Questionnaire-Current (SCQ)(Rutter et al. 2003) and/or the Social Responsiveness Scale-2 (SRS) (Constantino 2012) with scores < 16 and < 70 respectively. In two cases, both the SCQ and SRS-2 were missing and these children were screened with the Pervasive Developmental Disorder subscale on the Child Behavior Checklist (CBCL) (Achenbach and Rescorla 2001) with scores < 70. Two children were excluded based upon these criteria and another because the

caregiver reported a previous diagnosis of social pragmatic communication disorder.

57 children with ASD received a diagnosis from a research reliable clinician at CADB and completed the Autism Diagnostic Observation Schedule (ADOS) (Lord et al. 2012a) at CADB prior to participation. Diagnoses were based upon standard cutoff criteria for autism spectrum on the ADOS as well as clinical judgment.

The final sample for analyses was 124 children, 68 typically developing children ages (2.5–7.9 years, mean age = 5.0 years, 30 females) and 56 children with ASD (3.1–8.8 years mean age = 5.4 years, 11 females) (Table 1). Some children were excluded for poor behavioral performance, which is described below.

Behavioral Assessments

Cognitive abilities were assessed in TD children and ASD children with the Differential Ability Scales-Early Years or School Age (Elliott 2007). A subset of 4 children were assessed with the Mullen Scales of Early Learning (Mullen 1995), 1 child with the Stanford Binet (Roid 2003), 2 children with the Wechsler Preschool and Primary Scale of Intelligence (WPPSI)(Wechsler 2012) and 1 child with the Ravens (Raven et al. 2003) depending on age and developmental ability. Most children had scores that fell within standardized norms; for children with ASD that did not, ratio IQs were calculated. These were calculated by dividing each individual's mean 'age equivalent' by the individual's chronological age and multiplying by 100. A verbal IQ (VIQ) and non-verbal IQ (NVIQ) score was generated for each child. One ASD child was missing cognitive scores and was excluded from analyses with this measure.

In order to compare autism severity across children with ASD, calibrated severity scores (CSS) were generated from the ADOS (Lord et al. 2012b). The CSS is scored from 1 to 10 with 1 reflecting little to no symptoms and 10 reflecting severe symptoms. The CSS has a total score which demonstrates overall ASD symptoms, as well as Social Affect (SA) and Restricted and Repetitive Behaviors (RRB) totals (Hus et al. 2014), which divide symptom severity into the two core ASD domains.

Caregivers of TD children and children with ASD completed the Social Responsiveness Scale (SRS-2) (Constantino 2012) to measure general social communication symptoms. Total T-scores on the SRS were calculated and used for analyses. The SRS was missing in 6 ASD and 2 TD participants and these individuals were excluded only from analyses with the missing measure. Prior work has suggested that the SRS also captures problem behaviors in addition to general autism symptoms (Hus et al. 2013), so we collected the Child Behavior Checklist (CBCL) from caregivers to measure general problem behaviors and used the total problem behavior T score as a covariate only in analyses with the SRS-2. One child with ASD and 3 TD children were excluded only from analyses involving this measure because they were missing the CBCL.

Learning Task and Procedure

Children performed the learning task on an iPad, which allowed for flexibility. To ensure motivation, children "chose their adventure" from 11 different themes that were created from developmentally appropriate popular cartoons and movies. Upon choosing a theme, children completed 12 practice trials in which they were instructed to touch a "target" image and to refrain from touching the screen to any other images that were presented. Practice trials had a large red "X" covering the non-target image.

Experimental trials were made up of a sequence of two images that were each presented for 2000 ms (Fig. 1). One of two cues appeared followed by either the target or distractor image. Unbeknownst to the participant, the target was preceded by the high frequency (HF) cue and low frequency (LF) cue appearing at differing probabilities. In the HF condition, 75% of the time, the cue was followed by the target (63 trials) and 25% of the time, the cue was followed by the distractor (21 trials). In contrast, in the LF condition, 25% of the time, the cue was followed by the target (21 trials) and 75% of the time, the cue was followed by the distractor (63 trials). Thus, there were 84 trials in each condition (high and low frequency), divided into 7 runs of 24 trials each. A child started each trial by pressing a green button at the bottom of the screen. The button had to remain pressed until either the target or distractor appeared. Having the child press the button enabled each trial to be self-paced, and standardized the location of the child's hand before the target image appeared. Trial order was randomized for each participant, with the images used for the cues randomized across participants for each theme.

In between each run, children saw a 10 s movie clip associated with the theme they had chosen. Children were also given a sticker to put on a "visual roadmap" of the 7 runs. Because trials were self-paced, children could be given as

Table 1 Demographics for participants included in learning task analyses; mean (standard deviation)

	N	Age	VIQ	NVIQ	SRS	CSS SA	CSS RRB
TD	68	5.01 (1.35)	112.12 (16.8)	112.13 (18.3)	45.46 (5.8)	n/a	n/a
ASD	56	5.39 (1.34)	101.18 (17.5)	106.46 (21.1)	66.56 (10.0)	7.79 (1.6)	7.14 (2.0)

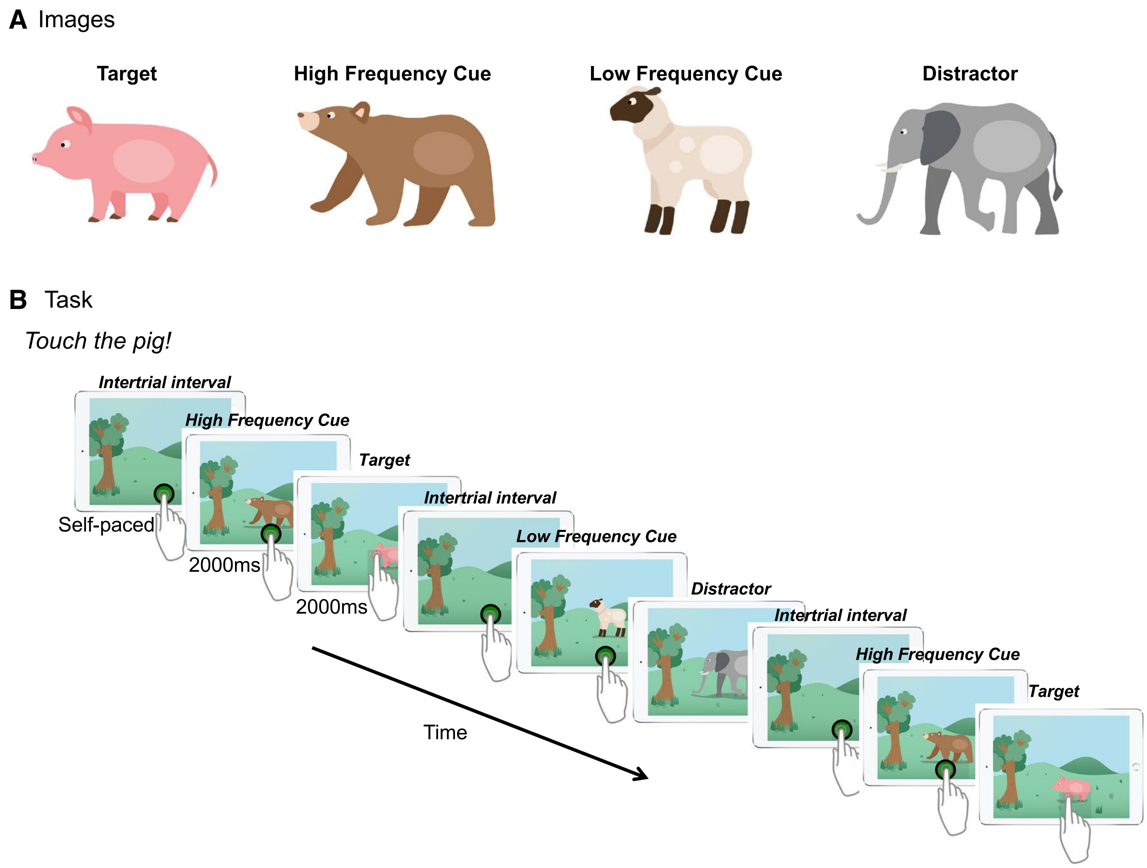

Fig. 1 Visual statistical learning task. The animal cartoons are *representative* placeholders as images were from popular cartoons and movies. **a** Children saw four different images. The high frequency cue preceded the target at a 75% probability and the distractor at a 25% probability. The low frequency cue preceded the target at a 25% probability and the distractor at a 75% probability. **b** Task sequence. Each trial was self-paced and started when the child pushed a button on the iPad and were instructed to keep their finger on the button until either the distractor or target appeared, at which point they were told to touch only the target. Cues and targets were displayed for 2000 ms

many breaks as needed and complete as many trials as possible until they became fatigued.

We attempted to collect data to determine whether children had explicit understanding of the contingencies in the task, by showing children pictures of the four characters before and after the task and asking them who the target character "played with". The data proved to be unreliable as many children had preconceived associations with the target and other characters. We do not report the data and future studies will need to determine how best to test for explicit understanding with this task.

Data Analysis

Analyses focused on the two dependent variables: accuracy and reaction times to the target for the first 21 trials in the HF and LF conditions. We chose to focus on the first 21 trials because there were only 21 trials where the cue was followed by the target in the LF condition, but there were 63 trials where the cue was followed by the target in the HF condition. Children were given 2000 ms to respond to the target and responses after this period were not recorded. Children with no responses to the target in the HF or LF conditions were excluded from analyses (1 ASD, 2 TD).

Accuracy

Accuracy was defined as correctly pressing to the target. Trials were divided into HF and LF conditions. First, a mixed-effects logistic regression ANOVA determined whether there were differences in accuracy across conditions (HF, LF) and group (ASD, TD). Second, analyses included an additional factor of trial number (1–21) to determine whether there were differences in accuracy across time for the two conditions in the two groups.

Reaction Times

We excluded reaction times that were < 350 ms as these were not likely deliberate responses (5 data points excluded).

Since reaction times were not normally distributed (skewed right), we used log-transformation to produce an approximately normal distribution. A model producing parabolic trajectories with quadratic and linear trend terms was used with the log-transformed reaction times as a function of trial number (1–21) to quantify the shape of the reaction time changes over time. A linear model would demonstrate a speeding or slowing in reaction times over time (Amso and Davidow 2012), whereas a quadratic model would show a speeding or slowing that was followed by the opposite in reaction time behavior (an 'U' or inverted 'U' shaped curve). Testing whether quadratic and/or linear terms fit the data in the two conditions (HF and LF) enabled us to assess whether there were differences in how the cue preceeding the target at either 75% or 25% influenced the pattern of reaction times over the course of the experiment. In this study, we have interpreted differences in reaction times over time for the HF versus LF to indicate learning. Models were selected by considering various subsets of predictors and trend terms using the Akaike Information Criterion (AIC). Lower AIC values correspond to a better model. The model included age of the participant, along with diagnosis (TD and ASD), type of trial (HF and LF) and linear and quadratic terms for trial number along with their interactions, as well as subject-level random effects for intercept and slope; maximum likelihood estimation was used to fit the model. A more detailed explanation of the model consideration and procedures are in Supplementary Materials. The software R was used to perform all analyses (*R: A Language and Environment for Statistical Computing* 2017).

Bayes Probability Classification

To determine the degree to which each child was able to learn during the task and to compare one child to another, we used a discriminant function based on Bayes probability of how well each child's reaction time patterns were similar to the TD group (Hastie et al. 2009). Belonging to the TD group was computed using bivariate normal density functions for the linear and quadratic trajectory coefficients (referred to as average slope and concavity measures respectively) from the ASD and TD groups; means for these densities were obtained from the estimated fixed-effects. How the slope and concavity measures were calculated are described in Supplementary Materials. The Bayes probability for the LF and HF conditions produced a continuous measure (on a scale of 0 to 1) for each participant of how similar or different each log-reaction time trajectory was to that of a TD child (0 not at all similar, 1 very similar).

We tested whether belonging to the TD group was contingent upon nonverbal and verbal IQ, age and autism symptoms. The association of the Bayes probability continuous measure to VIQ, NVIQ, age, SRS T scores and CSS SA and CSS RRB scores was examined using a nonlinear model (a logistic function) regressing the Bayes probability on these variables individually for the LF and the HF conditions separately.

Results

Accuracy

There were no differences in accuracy between the HF and LF conditions ($p = 0.368$) or between TD children (Mean HF = 0.824, Mean LF = 0.816) and children with ASD (Mean HF = 0.778, Mean LF = 0.784) ($p = 0.160$), nor was there an interaction ($p = 0.298$). There were also no significant differences in accuracy between TD children and children with ASD for the two conditions across the 21 trials ($p = 0.148$), suggesting no changes in accuracy over time. Together these results suggest that all children understood the instructions, completed the task as intended and that changes in reaction times were not due to differences in accuracy.

Reaction Times

There were unique reaction time patterns in TD children versus children with ASD, indicated by significant interactions across conditions (HF, LF), and group with the linear and quadratic trends (Table 2). Specifically, TD children demonstrated a quadratic pattern in their reaction times in the LF condition that was not present in the HF condition ($t = -1.888$, $p = 0.059$). In other words, by the middle of the trials (around trial 10–11 on average) TD children were slower to respond to the target after seeing the LF cue. This pattern was not observed for the HF condition, which was a flat line, thus suggesting the two cue contingencies influenced behavior towards the target differently. Interestingly, TD children began to speed up in the LF condition during the later trials, and there was no difference in reaction times between the two conditions for the last few trials. This speeding at the end of the experiment demonstrates that with more trials, TD children picked up on the contingencies in the LF condition. This overall learning pattern in the LF condition produced a concave-down LF trajectory that was not present for the HF condition. Based upon these findings, an improved model (AIC = 395.1) retained only distinct linear ($t = 4.81$, $p < 0.001$) and quadratic ($t = -4.25$, $p < 0.001$) trends for TD children for the LF condition, which is summarized in Table 3. The HF and LF curves are depicted in Fig. 2.

Children with ASD demonstrated a distinct pattern of reaction time behavior compared to TD children. Using the improved model (Table 3), only a linear trend was retained for ASD ($t = -2.11$, $p < 0.05$) for both LF and HF conditions.

Table 2 Reaction times model 1: summary statistics from the best model selected using AIC (AIC = 399.4)

Model	Estimate	SE	t
Intercept	7.5020	0.0648	115.740***
Group (Typ Dev.)	− 0.1171	0.0346	− 3.398***
Age	− 0.0076	0.0009	− 8.229***
Trial	− 0.0052	0.0042	− 1.249
Quadratic	0.0002	0.0002	0.838
Group (Typ Dev.)*trial	0.0013	0.0055	0.243
Group (Typ Dev.)*quadratic	0.0000	0.0003	0.099
Condition (LF)*trial	0.0051	0.0040	1.267
Condition (LF)*quadratic	− 0.0003	0.0003	− 1.292
Group (Typ Dev.)*condition(LF)*trial	0.0122	0.0054	2.270**
Group (Typ Dev.)*condition(LF)*quadratic	− 0.0007	0.0003	− 1.888*

Significance codes ***p < 0.01, **p < 0.05, *p = 0.059

Table 3 Reaction times model 2: summary statistics with only significant terms chosen from Model 1 (AIC = 395.1)

Model	Estimate	SE	t
Intercept	7.5081	0.0630	117.509***
Group (Typ Dev.)	− 0.1157	0.0325	− 3.559***
Age	− 0.0076	0.0009	− 8.232***
Trial	− 0.0023	0.0011	− 2.112*
Group (Typ Dev.)*trial	− 0.0015	0.0040	− 0.415
Group (Typ Dev.)*quadratic	0.0002	0.0002	1.111
Group (Typ Dev.)*condition(LF)*trial	0.0177	0.0036	4.812***
Group (Typ Dev.)*condition(LF)*quadratic	− 0.0009	0.0002	− 4.252***

Significance codes ***p < 0.001, **p < 0.01, *p < 0.05

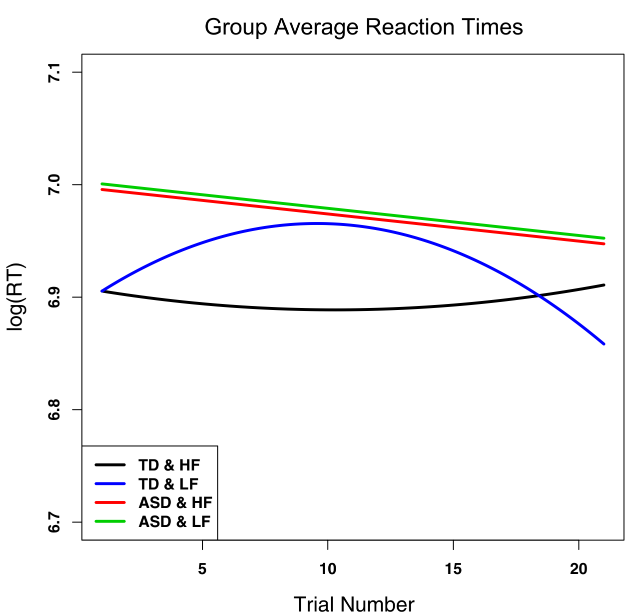

Fig. 2 Reaction time curves for the low frequency (LF) and high frequency conditions (HF) by diagnostic group

Depicted in Fig. 2, children with ASD demonstrated a downward linear trend in their reaction times for both the HF and LF conditions. There was no difference between the HF and LF reaction time curves, and no quadratic trend was evident. These ASD findings are in contrast to the TD children who demonstrated different patterns of learning for the HF and LF conditions.

As expected, younger children, regardless of diagnosis or condition, were slower on the task ($t = -8.232$, $p < 0.001$; Table 3). Also not surprising, TD children were faster on average (0.1164 ms) than children with ASD ($t = -3.559$, $p < 0.001$). Overall, reaction time curves differed significantly in shape between the LF and HF conditions for TD children, but not for ASD children.

Bayes Probability Classification

The slope and concavities were computed for HF and LF trials for all participants. Using a Bayes probability cutoff of 0.5 produces the elliptical discriminant boundaries shown in Fig. 3a. Individuals with ASD whose points fall

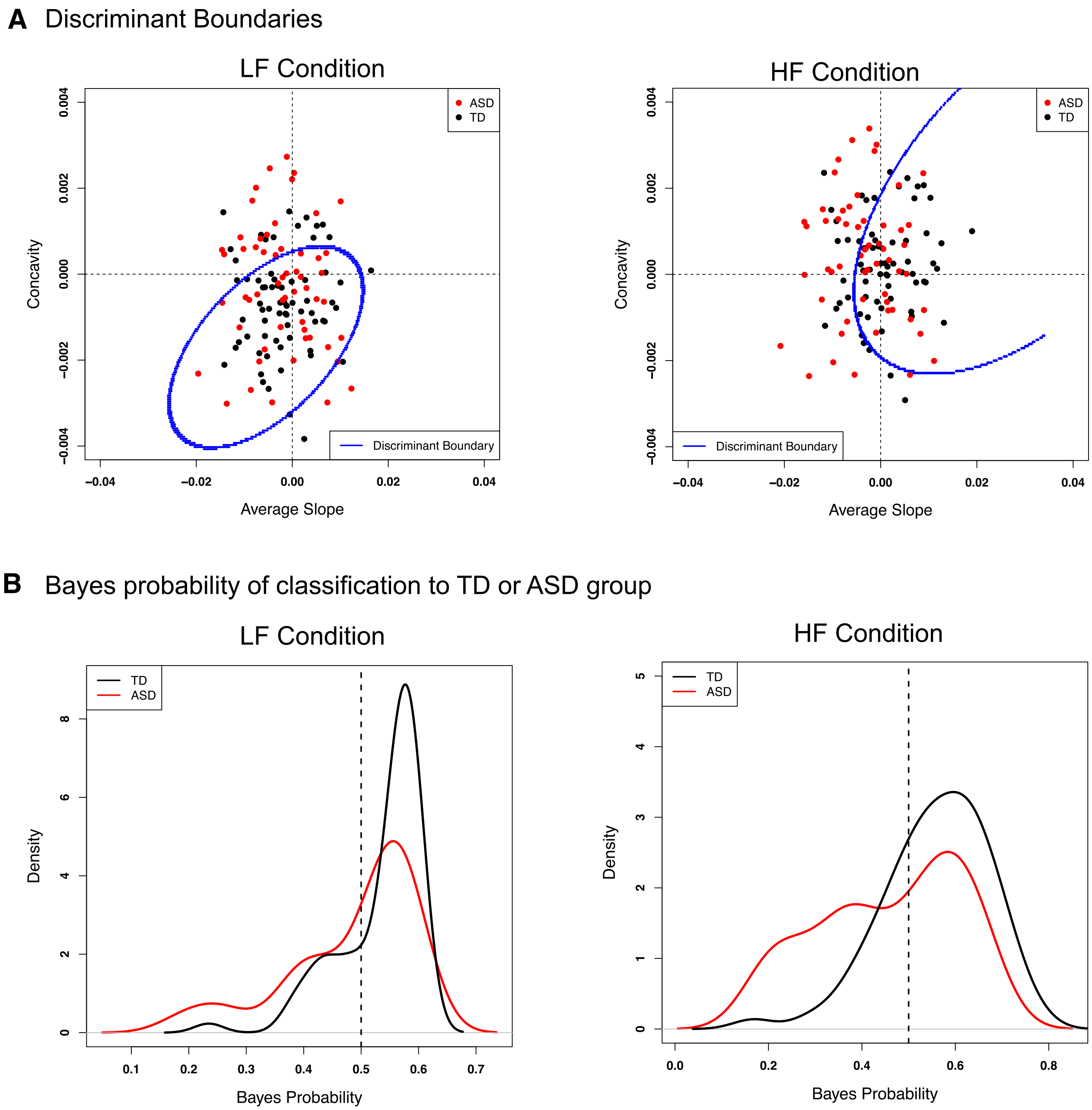

Fig. 3 Bayes probability classification. **a** Slope and concavity coefficients for the LF condition and HF condition in all children (red indicates children with ASD and black TD children). Ellipses (blue curves) represent discriminant boundaries (using a 0.5 probability cutoff) for classification as having a pattern similar to a TD child. **b** Density plots for Bayes probability classification as having a pattern similar to a TD child (right of dotted line) in the LF condition and HF condition. The red curve indicates density plot for ASD children and the black curve indicates density plot for TD children. (Color figure online)

inside the LF or HF ellipse have trajectories that are similar to those of TD children (using the Bayes probability cutoff of 0.5). There was a high degree of overlap between the ASD and TD children's distributions, with 34 children with ASD demonstrating a Bayes probability > 0.5 for the LF condition and 27 children with ASD demonstrating a Bayes probability > 0.5 HF condition, suggesting a large number of children with ASD performed similarly to TD children. As depicted in Fig. 3a, the elliptical boundaries demonstrate that for the LF trials, the difference between TD and ASD participants is reflected primarily in terms of positive and negative concavity, with a negative concavity suggestive of learning. The ellipise boundary for the HF trials demonstrate a different pattern where the difference between TD and ASD participants is reflected in the overall trend (i.e., average slope) rather than concavity. Figure 3b shows the nonparametric densities (smoothed histograms) of the Bayes probability for the LF and HF conditions. The density graphs depict the degree of overlap between ASD and TD children with data right of the dotted line suggesting learning. Whereas, data left of the dotted line is a pattern similar to children with ASD, demonstrating no evidence of learning. Together the findings suggest that many children with ASD, but not all, have a learning profile similar to that of a TD child.

Children with ASD with lower SRS scores were more likely to be classified as having a trajectory similar to a TD child for the HF condition ($p = 0.006$) but not the LF condition ($p = 0.789$) (Fig. 4). The association between the SRS and classification in the HF remained when controlling for total problem behaviors on the CBCL ($p = 0.0197$) and VIQ ($p = 0.0233$). In TD children, there was no relationship between SRS and classification of trajectories in the HF ($p = 0.458$) or LF condition ($p = 0.4272$).

Children with higher verbal IQ (regardless of diagnosis) were more likely to be classified as having a trajectory similar to TD children for the HF condition ($p = 0.0416$) with a weaker association for the LF condition ($p = 0.0788$) (Fig. 5). NVIQ, age, CSS SA, and CSS RRB were not associated with the likelihood of being classified as a TD trajectory for either the LF or HF conditions.

Discussion

The present study examined visual statistical learning in a young, heterogeneous group of children with ASD compared to TD children. On average, as a group, children with ASD appeared to have difficulty learning from regular patterns during a novel implicit learning task on an iPad compared to TD children. However, multivariate discriminant analyses demonstrated that many individual children with ASD (up to 34 children, 61%) showed behavioral patterns similar to TD children. These children with ASD who demonstrated clearer learning on the task had less severe autism symptoms. Together the findings suggest that simple learning abilities vary greatly in young children with ASD and therefore, statistical learning skills may begin to provide insight into some of the range of symptoms in ASD.

We defined learning in this task as demonstrating a difference in reaction time patterns over time to the HF versus LF conditions. In other words, TD children were slower to respond to the target that was preceded by the LF cue after multiple trials as compared to responding to the target after the HF cue. These findings are consistent with prior work (Amso and Davidow 2012) demonstrating a change in reaction times based upon probabilistic contingencies. By the end of the experiment, TD children demonstrated no difference between the two conditions. These findings suggest that TD children over time were able to pick up on less frequent patterns in the environment, but that it took more trials or presentations for them to do so. It is possible that with more

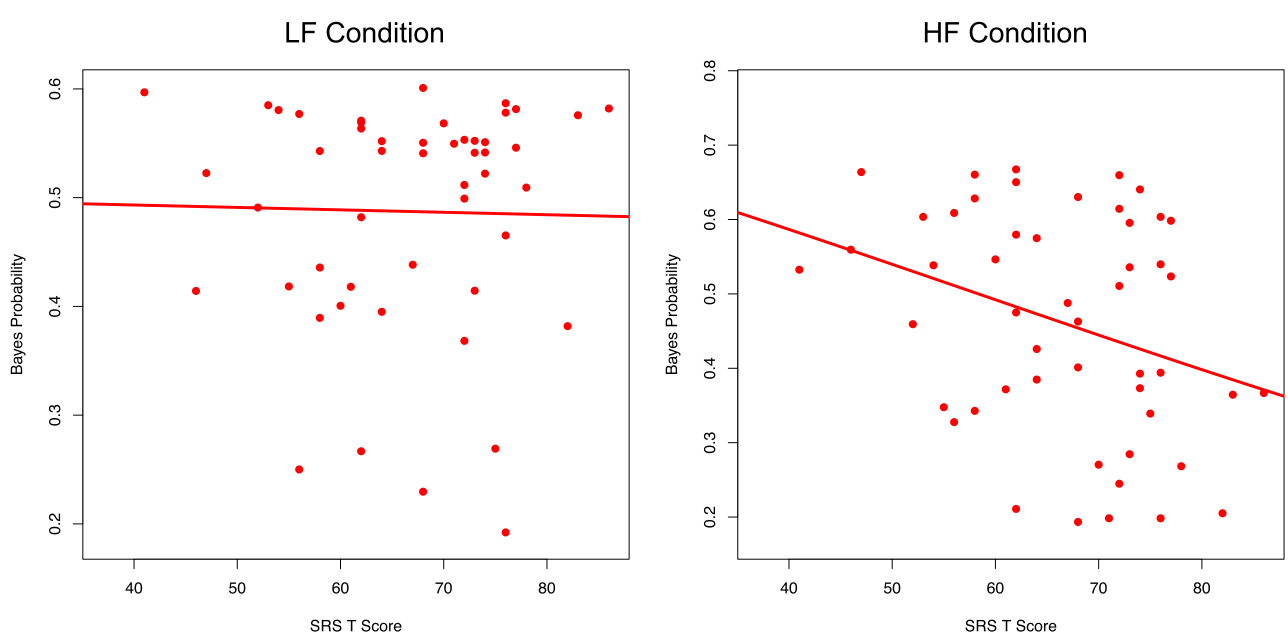

Fig. 4 Relationships between Bayes probability and autism symptoms measured by the SRS-2 T scores in the LF and HF conditions. There was a significant association with the SRS-2 in the HF condition and not the LF condition

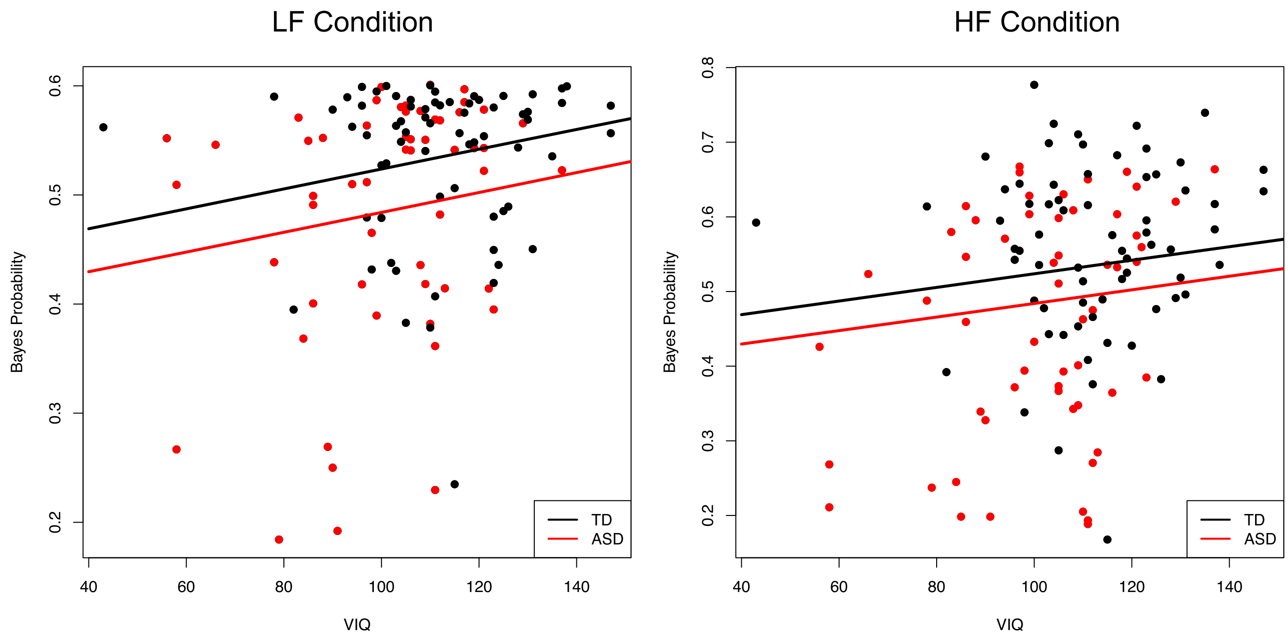

Fig. 5 Relationship between Bayes probability and verbal IQ. There was a relationship between verbal IQ and Bayes probabilities in both TD children (black points) and children with ASD (red points) in the HF condition with a weaker association in the LF condition. (Color figure online)

trials, more children with ASD, may have demonstrated differences between the HF and LF conditions (McGonigle-Chalmers and McCrohan 2017). However, it is important to note that TD children as a group demonstrated these differences around trial 10, and even with twice as many trials (up to 21), there was no pattern of differential learning in the group average of ASD children.

The findings in ASD are noteworthy in comparison to prior statistical learning tasks, where results have varied as to whether there are impairments in statistical learning in ASD (Foti et al. 2015; Gidley Larson and Mostofsky 2008; Gordon and Stark 2007; Mayo and Eigsti 2012). The Bayes classifications demonstrated that there was a range in learning abilities in the children with ASD, with many demonstrating patterns similar to TD children. Thus it is possible that the discrepancies in the literature simply have to do with the sample of children in the study, i.e. capturing a subset of homogeneous children or as our results suggest, a random sample of children will have variable learning skills. Our results also illustrate that averaging data across individuals has limitations because it masks underlying differences among children.

There was a relationship between statistical learning and general autism symptoms in children with ASD. The SRS-2 measures both social communication symptoms and restricted repetitive behaviors in children with ASD. Prior work suggests that the SRS-2 is also sensitive to the child's general problem behaviors (Hus et al. 2013). The relationship between statistical learning and the SRS remained when controlling for problem behaviors, suggesting that the association with learning was related to core ASD symptoms. It is possible that impairments in statistical learning may be a related to a deficit in picking up on visual cues in the environment that results in difficulties with complex social communication. Interestingly, there was no association with symptoms measured on the ADOS and statistical learning, perhaps because there was not enough variability in the CSS scores. There was also no relationship in TD children between SRS scores and statistical learning likely due to a restricted range in SRS scores in TD children. Future work measuring more fine-grained subsets of social communication or restricted and repetitive behaviors will be important for understanding how learning abilities relate to subgroups of children with ASD.

Statistical learning skills were associated with verbal IQ in both TD children and those with ASD. Interestingly, there was no association with non-verbal IQ. As verbal IQ was associated with statistical learning in both TD and ASD children, it is likely there is a common mechanism across diagnosis, where the associative learning skills tested in this task directly map onto expressive and receptive language abilities. We purposely did not match the ASD and TD samples on IQ, to capture diversity in children with ASD. It is important to note that in the TD sample, cognitive scores were somewhat above average. While we aimed to recruit a community sample, it is a limitation that the TD group is not necessarily representative of the normative mean. However, future research that examines children with developmental delays without ASD could more definitively confirm that the relationship with verbal IQ and statistical learning is unrelated to autism symptoms.

There are potential treatment implications from the present findings. Statistical learning is a foundation of the majority of behavioral interventions used in children with ASD such as applied behavior analysis (ABA), pivotal response training (PRT) and the early start denver model (ESDM). We observed that some children with ASD have intact learning abilities (at least in this context), while others did not, thus it is possible that statistical learning skills could in part contribute to why children differentially respond to early interventions based on behavioral principles (Kim et al. 2015; Rogers et al. 2012).

Conclusions

We designed an engaging statistical learning task that young, less cognitively able children with ASD were able to complete on an iPad in part because of flexibility in the task in content and pacing. Nevertheless, when comparing TD children versus children with ASD, it appeared that many children with ASD had difficulty learning on the task. Bayes probabilities that quantified individual children's patterns of learning demonstrated that a subset of children with ASD looked similar in their learning patterns to TD children. These findings highlight the variability inherent to the autism spectrum, variability that may be critical for understanding the range in responses to early behavioral interventions in ASD. Ultimately, identifying distinct learning patterns in young children with autism could be enlisted to tailor and inform treatment decisions.

Acknowledgments We thank Sara Levitt Palencia for her helpful input and feedback and thank Jennifer B. Schwartz for designing the illustrations in Fig. 1 (http://www.Jenniferbschwartz.com).

Author Contributions RMJ and CL developed the study. RMJ, GJB and CL contributed to the study design. Testing and data collection was performed by RMJ, AH and CC, TT performed the data analysis with the supervision of RMJ and CL, RMJ drafted the manuscript and CL and TT provided critical revisions. All authors approved the final version of the manuscript for submission.

Funding This study was funded in part by an Autism Speaks Meixner Fellowship (7608), the Department of Defense (AR130106), a generous gift from the Mortimer D. Sackler family and the Leon Levy Foundation.

Compliance with Ethical Standards

Conflict of interest Catherine Lord receives royalties from the ADOS and all proceeds related to this project were donated to charity.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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