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RESEARCH ARTICLE

# Structural and contextual priors affect visual search in children with and without autism

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**Abstract**

Bayesian predictive coding theories of autism spectrum disorder propose that impaired acquisition or a broader shape of prior probability distributions lies at the core of the condition. However, we still know very little about how probability distributions are learned and encoded by children, let alone children with autism. Here, we take advantage of a recently developed distribution learning paradigm to characterize how children with and without autism acquire information about probability distributions. Twenty-four autistic and 25-matched neurotypical children searched for an odd-one-out target among a set of distractor lines with orientations sampled from a Gaussian distribution repeated across multiple trials to allow for learning of the parameters (mean and variance) of the distribution. We could measure the width (variance) of the participant's encoded distribution by introducing a target-distractor role-reversal while varying the similarity between target and previous distractor mean. Both groups performed similarly on the visual search task and learned the distractor distribution to a similar extent. However, the variance learned was much broader than the one presented, consistent with less informative priors in children irrespective of autism diagnosis. These findings have important implications for Bayesian accounts of perception throughout development, and Bayesian accounts of autism specifically.

**Lay summary:** Recent theories about the underlying cognitive mechanisms of autism propose that the way autistic individuals estimate variability or uncertainty in their perceptual environment may differ from how typical individuals do so. Children had to search an oddly tilted line in a set of lines pointing in different directions, and based on their response times we examined how they learned about the variability in a set of objects. We found that autistic children learn variability as well as typical children, but both groups learn with less precision than typical adults do on the same task.

**KEYWORDS**
autism spectrum disorder, Bayesian brain, ensemble perception, perceptual learning, predictive coding, summary statistics, visual search

## INTRODUCTION

Bayesian predictive coding theories have recently gained traction as an explanation for autistic behavior, both in controlled lab settings (e.g., Karvelis et al., 2017; Lawson et al., 2017; Lieder et al., 2019) and as symptom clusters in daily life (e.g., Lawson et al., 2014; Palmer et al., 2017; Pellicano & Burr, 2012; Van de Cruys et al., 2014). In these theories, perception and learning are cast as probabilistic inferences combining prior knowledge with perceptual inputs (likelihood). More specifically, predictive coding assumes that priors and likelihoods are represented as Gaussian probability distributions (Friston & Kiebel, 2009), characterized by a mean (the expectation) and a precision (inverse variance; the width of the bell-shape). The extent to which perceptual estimates (decisions) are biased toward the actual evidence versus the prior is determined by the relative precision of the respective distributions. Importantly, both the means and the precisions of the prior distributions need to be estimated or learned through experience (Hohwy, 2013). Indeed, the many proposals on what inferential processes go awry in autism converge on how precisions are estimated and shaped by experience. For example, keeping the sensory precision constant, a prior with lower estimated precision is broader and has a weaker effect on perception. Usually, however, informative priors provide the necessary robustness to perception, allowing us to exploit known regularities and discard the noise, in order to zoom in on behaviorally relevant changes (prediction errors) in the input (Van de Cruys et al., 2017). Hence, a failure to learn and apply informative priors may lead to unstable, more variable percepts (cf. hypersensitivity) and problems selecting relevant input dimensions in the face of (noise) variability in other dimensions (crucial in social settings). In the longer term, this inability to "regularize" perception may elicit compensatory behavioral strategies in terms of repetitive movements and other ways to recover a modicum of predictability in perceptual inputs (cf. insistence on sameness). In short, there is a plausible etiological chain from problems in estimating precision to the key symptom clusters in autism spectrum disorder (ASD), described as impairments in social interaction and communication on the one hand, and repetitive and restrictive behaviors and interests, including alterations in sensory sensitivity, on the other hand (American Psychiatric Association, 2013).

Research on summary statistics, also known as ensemble perception, has shown that people have no problems extracting the means of sets of stimuli, be it based on low-level features such as orientation or size, or higher-level features such as face identity and emotional facial expressions (Whitney et al., 2014; Whitney & Yamanashi Leib, 2018). Representing a set of stimuli by its average often happens without being able to recognize each individual item of the set and is even present under conditions of reduced attention. Previous research on ensemble perception in ASD yielded mixed results. Children (Van der Hallen et al., 2017) and adults (Corbett et al., 2016) seem to be able to represent sets of dots by their mean size. Children with ASD may even tolerate more variability when estimating averages (Manning et al., 2015; Van der Hallen et al., 2017). Yet another study found no difference in the ability to represent the average emotion of faces between children with and without ASD (Karaminis et al., 2017; but see Rhodes et al., 2015).

In addition to ensemble means, ensemble variance has been found to be extracted for size and orientation in neurotypical adults (Norman et al., 2015; Solomon, 2010), but has been studied less compared to the average of sets of stimuli. Even so, we know that extracting variance is a prerequisite for many odd-one-out visual search tasks. Indeed, to find an item that does not belong to a set (detect an outlier), it is crucial to know the diversity or variability of the items that *do* belong to the group (Haberman & Whitney, 2012; Rosenholtz, 2001). Moreover, an estimate of the variance of groups of stimuli provides the observer information on the reliability or precision of the average of the set. To the best of our knowledge, no studies have verified whether variance extraction is already present in children (with or without ASD).

In the current study, we use odd-one-out visual search as an implicit measure of whether children extract variances. Rather than explicitly asking participants for estimates of summary statistics as in most studies on the topic, Chetverikov et al. (2016, 2017a, 2017b, 2017d, 2020) developed a method to infer the representation of those statistics from visual search performance, arguably a more ecologically valid way to probe this. They based their paradigm on findings of priming of pop-out, a phenomenon that occurs when an odd-one-out target has the same features over different visual search trials, leading to decreased response times. Priming of pop-out has also been found when distractors have the same features over different trials. Chetverikov et al. used such priming, in addition to role reversal—when a target falls within the feature distribution of distractors in previous trials—to infer to what extent the distributions of the distractor set (their mean, variance, and shape more broadly) are encoded implicitly. Using this method, Chetverikov et al. (2016, 2017b, 2020) reported that our visual brain not only extracts and represents the first-order statistics such as the average but also various other properties of the distributions, such as variance, type (e.g., normal vs. uniform) and skewness.

The visual search paradigm by Chetverikov and colleagues is extremely suited here for several reasons. First, while concepts such as mean and variance may be difficult to grasp for children, a visual search task is very intuitive. Second, visual search is known to be intact or even improved in ASD from very early on in development (Kaldy et al., 2011; Van der Hallen et al., 2015). Any impairments or alterations in performance are unlikely to be explained by the basic nature of the task.

Third, the paradigm allows us to look at the role-reversal effect in which the target suddenly falls within the previously learned distractor distribution range. Plotting the participants' response times as a function of the difference between the current target orientation and the previous distractor distribution mean will show the shape of the represented prior distribution (its variance or inverse precision), as learned across repetitions of the same (distractor) distribution. Here, we can address questions concerning the aberrant estimation of precision, as proposed by predictive coding accounts of ASD (Lawson et al., 2014; Pellicano & Burr, 2012; Van de Cruys et al., 2014). Specifically, we will be able to examine whether the learned distractor distribution is broader or narrower than the actually presented Gaussian distractor distribution. Note that there is some vagueness in the existing theoretical proposals as to what to expect: Some merely state that the estimated precision is "aberrant" in autism (Lawson et al., 2014), others suggest that the precision of prediction errors is higher (Brock, 2012; Constant et al., 2018; Van de Cruys et al., 2014), which should lead to more precise posteriors and, subsequently, priors (because today's posterior is tomorrow's prior). Yet others made a clear claim that priors in autism are less precise (Pellicano & Burr, 2012).

Fourth and finally, in the literature on Bayesian predictive coding, a distinction is made between structural and contextual priors (Seriès & Seitz, 2013; Teufel & Fletcher, 2020). Contextual priors are based on regularities specific to a particular context, for example, predicting the next word in a sentence based on the semantic and syntactic structure. These priors are assumed to be learned and deployed in a hierarchical way with predictions from one level predicting input activity in the level below. Such predictions usually have a more limited applicability, but can be quickly and flexibly learned through experience (Van de Cruys, Vanmarcke, Van de Put, & Wagemans, 2018). This is the type of prior we induce in our visual search paradigm, by repeating trials with the same distractor probability distribution.

Contrary to contextual priors that are learned in a short time span (in just a few trials), structural priors reflect innate or overlearned statistical regularities in the visual input. These priors are applicable across all visual inputs irrespective of context because they concern (quasi-)universal scene statistics. Instead of relying on the top-down connections between levels, they are thought to be encoded as embedded constraints in bottom-up information processing (Teufel & Fletcher, 2020). A common example is the light-from-above prior, which causes us to perceive ambiguous shading stimuli as lighted from above, as is usually correct for natural images. For orientation perception, it is well-known that people are much better at discriminating cardinal orientations (horizontal and vertical) compared to oblique orientations because the former are much more prevalent in our natural visual environment (Girshick et al., 2011). Given that we use sets of oriented lines as visual search displays, we will be able to verify in our study whether outliers (targets) are easier to spot when the distractor distribution mean is cardinal versus oblique, and whether this effect of the structural prior is reduced in ASD (if priors are broader), as one study already found (Dickinson et al., 2016; but see Shafai et al., 2015).

# METHODS

## Participants

Two groups of children between 10 and 14 years old participated in this study ($N$ = 49; M age = 11.94 years; $SD$ = 1.39; range: 10–14 years). Intelligence of the participants was estimated with an abbreviated version (Sattler, 2001) of the Wechsler Intelligence Scale, Third edition (WISC-III-NL; Wechsler, 1992). From this abbreviated version, a performance intelligence quotient (PIQ), a verbal intelligence quotient (VIQ), and a full-scale IQ (FIQ) are derived. Based on these results, none of the participants had an intellectual disability (FIQ ≤70). All participants had normal or corrected-to-normal vision and none reported taking any neuroleptics.

The ASD group consisted of 24 children diagnosed with ASD by a child psychiatrist or a multidisciplinary team, based on the DSM-IV-TR criteria (American Psychiatric Association, 2000). Participants were recruited via the Autism Expertise Centre of our university hospital. In proportion to the gender ratio described in the literature (Lai et al., 2015), the ASD group comprised 8 girls and 16 boys. The ASD diagnosis was re-evaluated using the Autism Diagnostic Observation Schedule 2, Module 3 (ADOS-2; Gotham et al., 2007), conducted by a trained psychologist. Eighteen participants scored above the ASD cut-off and six participants below the ASD cut-off on the ADOS-2 (Mean = 8.76, $SD$ = 4.17). Moreover, ASD traits were measured with the Dutch version of the social responsiveness scale (SRS-2; Roeyers et al., 2011). In addition, the Dutch version of the sensory profile questionnaire (SP-NL; Dunn & Rietman, 2006) was administered to measure how the children process sensory information in everyday situations. We assessed the level of attention problems (and emotional or behavioral problems) by administering the child behavior checklist (Achenbach & Ruffle, 2000) parent report to control for the influence of attention problems on-task behavior. The typically developing (TD) group consisted of 25 children recruited through mainstream schools. The TD participants did not have a known diagnosis of a child psychiatric disorder nor they did have a first-degree family member diagnosed with ASD. Demographic details and $p$-values of a two-sided $t$-test for the comparison of the ASD group and the matched TD group are shown in Table 1.

## Procedure

This study was approved by the ethical committee of the university hospital and incorporated within a larger series of studies on visual perception in children with ASD. Parent consent and child assent were given before the start of the test session. The tests took place in a quiet and darkened room and the viewing distance was ~57 cm.

The odd-one-out visual search task was presented to the children as a space game in which they could discover a new planet by following the stars falling in the oddest direction. The participants had to search for the odd-one-out in a 6 × 6 grid of 36 lines subtending 16° × 16° at the center of a display (see Figure 1). Each line represented a

**TABLE 1** Participant characteristics

| | ASD (16 male: 8 female) | | TD (13 male: 12 female) | | Two-sided *t* test |
|---|---|---|---|---|---|
| | M | *SD* (range) | M | *SD* (range) | *p*-value (BF10) |
| Age | 12 | 1.30 (10–15) | 11.85 | 1.50 (10–15) | 0.62 (0.32) |
| Verbal IQ | 105 | 17.67 (57–130) | 105 | 10.86 (68–122) | 0.92 (0.29) |
| Performance IQ | 106 | 17.23 (74–132) | 107 | 14.09 (66–143) | 0.76 (0.30) |
| CBCL attention | 58.20 | 7.92 (50–77) | 54.67 | 5.88 (50–66) | 0.12 (0.85) |
| SRS-2 | 89.33 | 16.99 (52–119) | 49 | 8.61 (38–65) | <0.0001 (>100) |
| ADOS | 8.62 | 4.06 (1–19) | | | |

*Note:* SRS data of three participants with ASD and of four TD participants is missing.
Abbreviations: ADOS, autism diagnostic observation schedule; BF10, bayes factor; CBCL, child behavior checklist; SRS-2, social responsiveness scale.

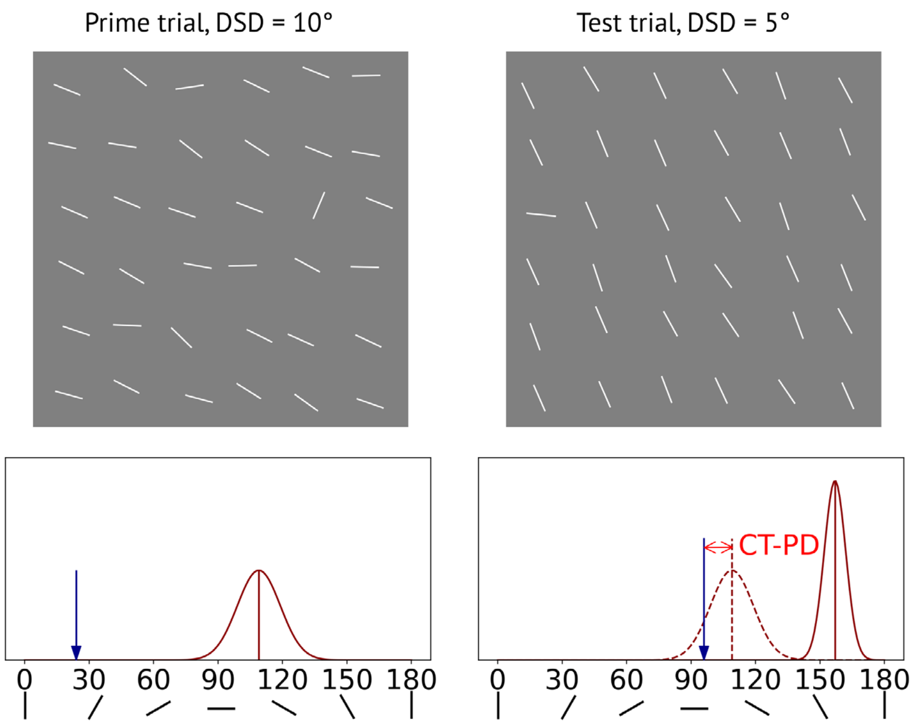


**FIGURE 1** Example search array for a prime trial and example search array for a test trial. In the prime trial (left side), the distractors are sampled from a Gaussian distribution with a distractor distribution standard deviation (DSD) of 10° (dark red). In this example, the mean orientation (vertical line in the bell-shape) of the distribution is 109° and the target orientation (blue arrow) differs 85° from the distractor distribution mean. In the test trial (right side), the distractors are sampled from a Gaussian distribution with a DSD of 5°. The previous distractor distribution is represented in dashed lines. In this example, the difference between the current target orientation (blue arrow) and the previous distractor distribution mean (CT-PD) is 13° (red double arrow). The target differs 61° from the current distractor distribution mean (M = 157°; in dark red)

falling star and the length of each line was 1.41°. All line positions were jittered by randomly adding a value of ±0.5° to vertical and horizontal coordinates. The participants used the arrow keys to indicate whether the target was in the upper or lower half of the display (little dots on the side of the search array indicated the division).

The children were encouraged to respond as fast and accurately as possible and received a score after each response, indicating how close they got to the undiscovered planet. The children were told that there was another competing team of astronauts with the same mission. Every 10 blocks (±70 trials), a screen was presented with their own score as well as the score of the competing team of astronauts (a random number of points below the participant's score). The children could take a self-paced break here.

Before starting with the actual test trials, the participants completed an extensive step-by-step practice protocol with 10 practice trials, with feedback on all trials. During the actual experiment, feedback was only provided for incorrect trials.

## Apparatus and stimuli

Trials were organized in blocks consisting of a prime streak and a test streak. A prime streak consisted of five or six trials with distractor orientations sampled from the same distractor distribution with a constant mean and *SD*. The trial number was varied to prevent participants from learning the regularities in changes from prime streaks to test streaks throughout the experiment. The distractor distribution in trials in prime streaks was always a Gaussian distribution, with a distractor standard deviation (DSD) of 10°. The mean of the distractor distribution was set randomly for each prime streak. The target orientation was set randomly for each trial within the prime streaks, with the constraint that the difference between the target orientation and the mean of the distractor distribution could range from 60° to 120°. During the prime streaks, the mean of the distractor distribution and the DSD (always 10°) remained constant, whereas the target orientation and location differed on every trial.

Each prime streak was followed by a test streak consisting of one to two trials with the distractor orientations sampled from the same distractor distribution. The test streak distractor distribution was a Gaussian distribution with a DSD of 5°. The target orientation in the test trials differed −90° to 90° from the distractor distribution mean of the previous prime streak. The difference between the *current target* orientation in the test trials and the *previous distractor* distribution mean (CT-PD) was randomly chosen out of the 13 bins with different bin sizes (i.e., smaller bin sizes closer to zero). The different CT-PD bins were (−90° to −70°), (−70° to −50°), (−50° to −35°), (−35° to −25°), (−25° to −15°), (−15° to −5°), (−5° to +5°), (+5° to +15°), (15° to 25°), (25° to 35°), (35° to 50°), (50° to 70°), and (70° to 90°). Bin sizes were smaller where the target orientation was closer to the previous distribution mean (i.e., small CT-PDs), to have a higher precision for our response times plotted as a function of CT-PD in the area around the previous distribution mean.

Each prime streak length (five or six trials) was followed by a test streak with a target orientation chosen based on a CT-PD sampled from each CT-PD bin, so together prime and tests streaks formed blocks of six to eight trials. These combinations were repeated five times per participant, resulting in 130 blocks (13 orientations × 2 streak lengths × 5 repeats) per participant, or ∼910 trials. The total test session duration was between 20 and 40 min, depending on the self-paced breaks.

# ANALYSIS

All experiment code, data, and analyses (including extra analyses) can be found at the Open Science Framework (osf.io/95672). For all analyses, response time data were log-transformed to reduce skewness. In all response time analyses, only correct trials are included. Per participant, response times of three *SD* higher than this person's mean response time and response times lower than 100 ms were removed from the analysis. Based on these outlier criteria, 1.9% of all trials were removed for the ASD group and 2.1% of all trials were removed for the TD group. Bayes factor versions of the reported mixed models analysis of variance (ANOVA) can be found in the Supplementary Materials.

# RESULTS

## Average visual search performance

A linear mixed model (random intercept and random slope model) with *DSD, Group* and *Group x DSD* as predictors, revealed a significant effect of *DSD* on search times ($B = 0.08$, $t = 5.01$, $p < 0.0001$), with shorter search times in the test streaks with a *DSD* of 5° (M = 1138 ms, *SD* = 686) compared to search times in the prime streaks with a *DSD* of 10° (M = 1290 ms, *SD* = 1058). Neither the effect of *Group* ($B = 0.03$, $t = 0.6$, $p = 0.55$) nor the interaction effect between *Group* and *DSD* ($B = -0.008$, $t = -0.40$, $p = 0.69$) on search times was significant (see Figure 2). A generalized mixed model on the accuracies shows the same results qualitatively: only a main effect of *DSD* (more accurate for low DSD), not of *Group*. Furthermore, a Bayesian analysis on reaction times shows moderate evidence *against* including a main effect of *Group* and/or an interaction effect of *Group x DSD* (see Supplementary Materials for full results).

These results imply typical visual search performance in children with ASD, irrespective of the amount of variability in the display. However, a post hoc analysis showed a significant negative correlation of autism traits, as measured by the SRS-2, and mean response time in the visual search task (Pearson $r = -0.64$, $p = 0.001$, see Figure 3). To look at this in more detail, we plotted conditional accuracy functions (Figure 4) on quantile split data. They indicate that particularly in the lowest response time bins, people with high SRS-2 (but not with mid SRS-2) are faster in searching the displays, without paying in terms of accuracy. This suggests that the improved visual search performance sometimes found in other studies (see Discussion) may be limited to individuals with high autism traits and displays where serial search is not required.

## Structural priors

When looking at the effect of structural priors, one of our key questions, we find a pronounced curve which is characteristic for a strong effect of cardinal orientations

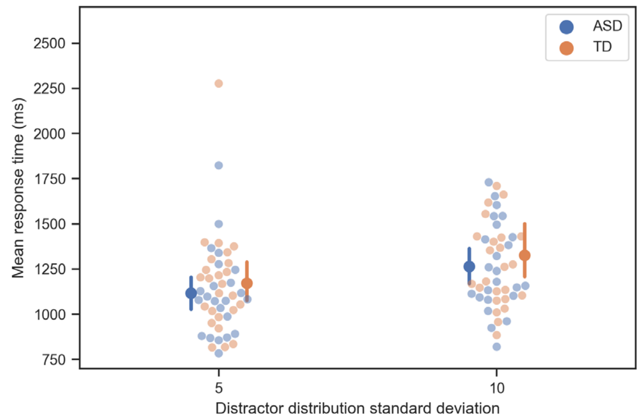


**FIGURE 2** Mean response times for the two distractor distribution conditions for both groups. Error bars represent 95% bootstrapped confidence intervals. Lighter dots represent individual means. Note that conditions have unequal trial numbers because of the design (5° are test trials, 10° prime trials)

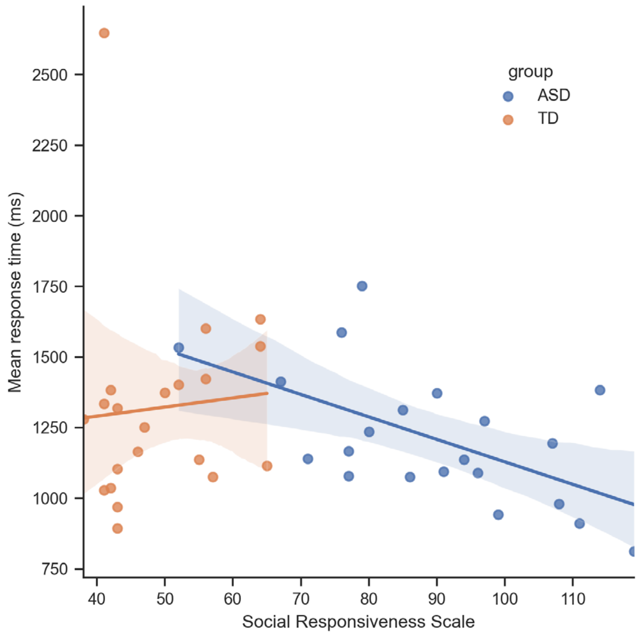


**FIGURE 3** Scatterplot of the social responsiveness scale-2 (SRS-2) score by mean response time in ms per participant, with linear fits and 95% confidence intervals (shaded areas) per group

($B$ = 7.00; $t$ = 11.1; $p$ < 0.001), similarly present in children with and without ASD (see Figure 5; $B$ = 1.27; $t$ = 0.94; $p$ = 0.35). We find faster target detection for targets with orientations around the horizontal or vertical axis compared to oblique targets.

## Repetition effect within prime streaks

We assessed repetition effects by analyzing response times and accuracy over trial numbers within prime streaks, in which the distractors at each trial were sampled from the same Gaussian distribution. A linear mixed model with *Trial Number*, *Group* and *Group x Trial Number* as predictors with Helmert contrasts for *Trial Number* (comparing average response time on each trial with the average response time on all subsequent trials) revealed significantly higher response times on the first trial compared to response times on the later trials for both groups ($t$ = 10.61, $p$ < 0.0001; see Figure 6). On the second trial, response times were not significantly different anymore from later trials, suggesting that virtually all learning took place from the first to the second trial in the streak. No effect of *Group* ($t$ = 0.42, $p$ = 0.68) or *Group x Trial*

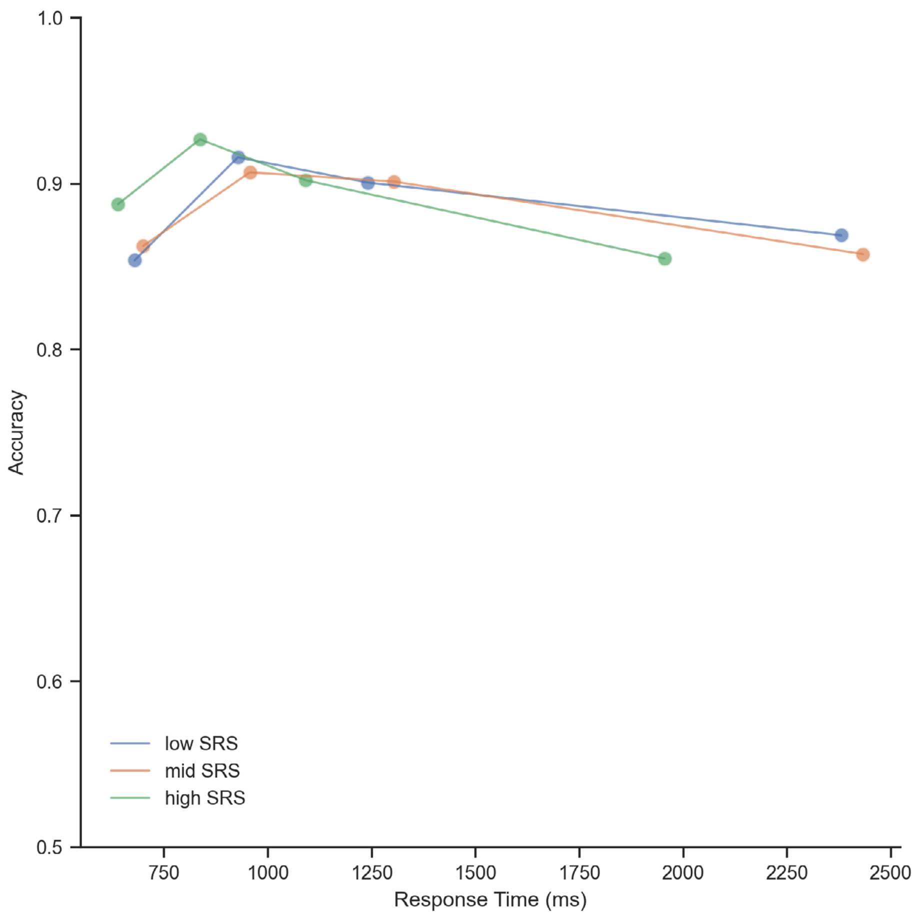


**FIGURE 4** Conditional accuracy functions per quantile split SRS-2 group: low SRS-2 (<52) with 13 TD participants; mid SRS-2 (between 52 and 80) with seven TD and six ASD participants, and high SRS-2 (>80) with 13 ASD participants. Each data point is the accuracy for a quartile of the response time distribution

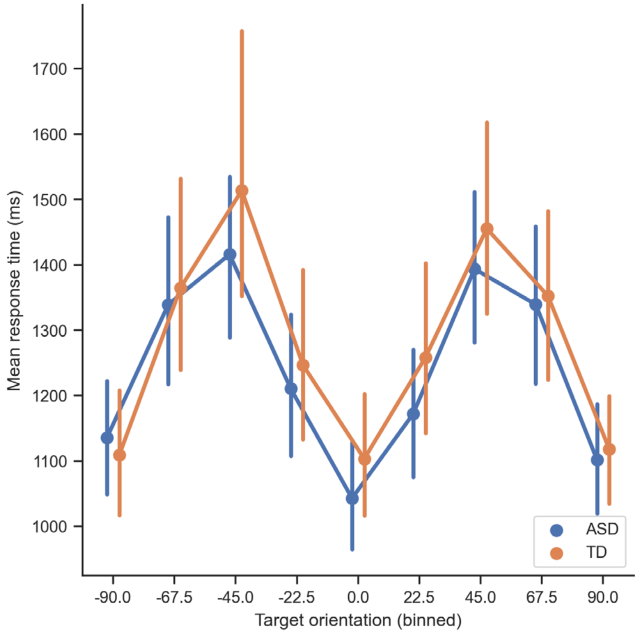


**FIGURE 5** Mean response time in ms for a given target orientation (binned), showing a clear effect of cardinal versus oblique orientations (collapsed across all trials/conditions). Error bars are 95% bootstrapped confidence intervals

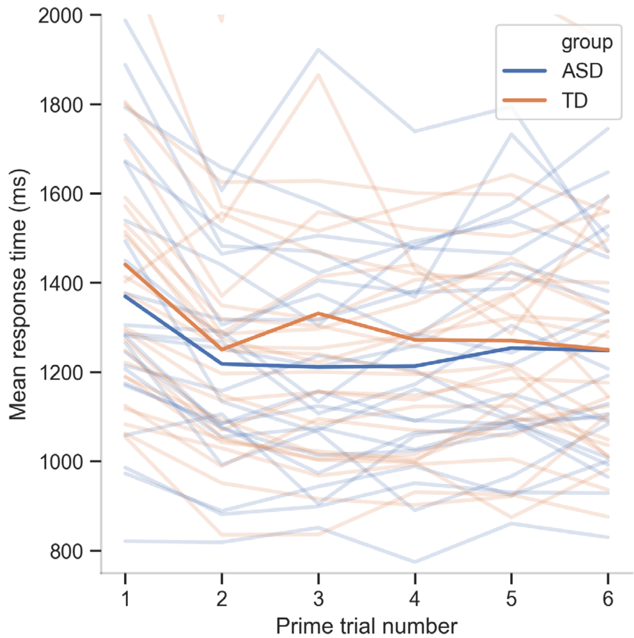


**FIGURE 6** Mean response times for each trial within prime streaks for both groups (darker lines). Lighter lines represent average response times for each participant

*Number* interactions were found. Accuracy did not change across trials. These results indicate a quick decrease in response times after one trial with distractors sampled from the same Gaussian distribution in both groups.

## Role-reversal effects

To test the role-reversal effects in test streaks, we analyzed response times on correct first trials of test streaks as a function of the distance between the current target orientation and the mean of the previous distractor distribution (*CT–PD*) (see Figure 7). If a distractor distribution is learned and therefore inhibited during repetitions in prime streaks, response times should increase when a target falls within that prime distribution in a test streak. Figure 7 shows that role-reversals have a strong effect in both groups, as response times gradually decrease with the increase of absolute CT-PD. A linear mixed model with *absolute CT-PD*, *Group*, and *Group x absolute CT-PD* as predictors and response time as an outcome variable revealed a significantly negative effect ($B = -0.05$ [0.01], $t = -5.47$, $p < 0.0001$) of *absolute CT-PD* on response time. No effect of *Group* ($B = 0.03$ [0.05], $t = 0.58$, $p = 0.56$) or interaction effect of *Group x absolute* CT-PD ($B = 0.01$ [0.01], $t = 0.19$, $p = 0.85$) was found. Again, a Bayesian analysis on reaction times shows moderate evidence *against* including a main effect of *Group* and/or an interaction effect of *Group x absolute CT-PD* (see Supplementary Materials for full results).

In typical adults, previous studies have shown that the fall-off of response times tracks the width (or type) of distribution closely (Chetverikov et al., 2016), indicating that a more or less faithful representation of the distribution was learned during prime trials. However, as can be seen in Figure 7, in our sample of children, response times only start to go down when CT-PD is outside of the full range of the normal distribution (beyond CT-PD = 25), suggesting that the shape of the distribution is not (fully) learned, but only represented as a range or uniform distribution. For comparison, Figure 7b shows data Chetverikov et al. (2016, Experiment 1) for neurotypical adults under the same distributional conditions. Indeed, if we apply the same analysis to the binned CT-PD (bins determined based on sampling frequencies in the experiment) only two last bins, well beyond the "primed" distribution, have significantly lower response times compared to average response times in previous bins (CT-PD = 50–70: $B = -0.08$, $t = -2.03$, $p = 0.047$; CT-PD = 70–90: $B = -0.12$, $t = -2.94$, $p = 0.005$).

Recoding CT-PD to a binary variable indicating whether the current target orientation fell within the range of the previous distractor distribution (*CT-PD* < 30°) or outside of it (*CT-PD* > 30°) revealed a significant effect of *In range* ($B = -0.10$ [0.02], $t = 5.91$, $p < 0.0001$) on response times, with lower response times for trials where the target orientation fell outside ($M = 1125$ ms) versus inside the previous distractor distribution range ($M = 1216$ ms). Again, no significant effect of *Group* or *Group* x *In range* interaction effect was found. Importantly, there is no effect of CT-PD on reaction times if we test this on the data of within range trials only ($B = 28.63$; $t = 0.88$; $p = 0.380$; no group

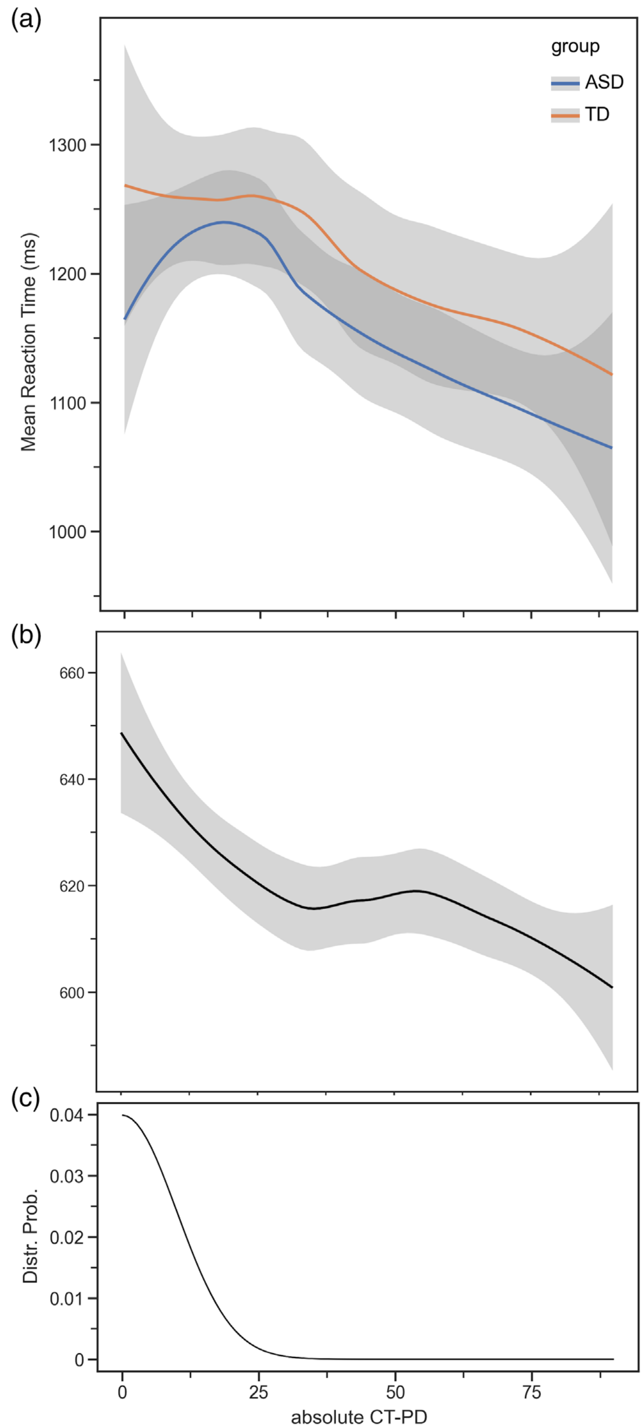


**FIGURE 7** Local regression fit of response times (shaded areas are 95% confidence interval) plotted as a function of the absolute distance between current target orientation and the mean of the previous distractor distribution (CT-PD, in degrees), for the ASD and TD group (a). The middle plot (b) depicts the same for typical adults, based on data from Chetverikov et al. (2016). The lower plot (c) represents (half of) the normal distribution ($SD = 10$) from which the distractors in the previous trials were actually sampled

interaction: $B = -79.27$; $t = -1.057$; $p = 0.29$), indicating that the slope in this range is not different from zero, which is inconsistent with the encoding of a Gaussian.

# DISCUSSION

Children with and without ASD performed a visual search task specifically developed to examine implicit perceptual distribution learning. While our groups did not significantly differ in overall visual search performance, people with strong autism traits were significantly faster in finding the target. Also, structural priors (oblique vs. cardinal orientations) strongly but similarly influenced search performance in both groups. In addition, both groups benefited equally from the fact that distractors are sampled from the same distribution as the previous trial(s). However, there does not seem to be much extra learning beyond the first repeat of that distractor distribution. Finally, through target-distractor role reversal, we could establish that the prior distribution that children learned was much broader than the actually presented distribution, suggesting that the variance cannot be properly learned in the number of trials in which adults properly can do so. While a few previous studies indeed found slower or less flexible learning of priors in adults with ASD (Lieder et al., 2019; Sapey-Triomphe et al., 2020; Zaidel et al., 2015), our findings here suggest that the less precise encoding of the prior distribution holds for all children, irrespective of ASD diagnosis.

Despite several reports of improved visual search in ASD, a meta-analysis showed no significant difference in performance (Van der Hallen et al., 2015). Still, three recent studies not included in the meta-analysis did find improved search in very young children (Cheung et al., 2018; Kaldy et al., 2011), with one study reporting that better visual search performance in nine-month-old infants predicts ASD traits at a later age (Gliga et al., 2015). Our study corroborates that relation between ASD traits and faster search performance, and might help to resolve inconsistencies in this literature. While visual search studies often use rather homogeneous distractor sets, we continuously varied the items in this set, which means the challenge of inferring "sameness" in order to find the outlier (odd-one-out) is greater here. This factor may explain the lack of the main effect of Group on overall search performance. Compared with adults in the same task, children are considerably slower (average of 675 vs. 1250 ms, see Chetverikov et al., 2016) suggesting the need to sample (saccade) across multiple (smaller) areas serially to correctly estimate means and variances and find the odd-one-out. Those processes may obscure any advantages in local search that children with autism may have. That said, our results do suggest that children with autism are more correct in the very short response times compared to typically developing children, implying that their capacity to process the dissimilarity as such might be increased (when they coincidentally land in the area of the target), in line with previous studies (Baldassi et al., 2009), but that this advantage is washed out if spatial pooling across multiple saccades is required. Alternatively, participants with ASD may already pool across a greater number of items in a single fixation (leading to better mean and variance estimates, and so better outlier detection), consistent with studies on motion direction discrimination (Manning et al., 2015, 2017).

With regard to the influence of structural priors, we found that they influence perception to a similar extent in autism and typical development (e.g., no broader priors here), consistent with what Shafai et al. (2015) found for a simple (single stimulus) orientation discrimination task (but see Sysoeva et al., 2015). Visual search was harder (slower) when targets were near the oblique orientations compared to near horizontal or vertical orientations (the so-called oblique effect), showing that these biases are already clearly apparent in children, irrespective of autism diagnosis. This is consistent with the evidence of another intact structural prior in children with and without autism, namely the light-from-above prior (Croydon et al., 2017). The faster search for targets around the cardinal orientations may be due to a disproportionately larger fraction of V1 neurons sensitive to cardinal orientations, with narrower orientation tunings (Girshick et al., 2011), so more precise encoding and possibly better discrimination in a search. However, it is possible that attractive biases, i.e. perceiving a stimulus to be more cardinal than it actually is because of the strong cardinality prior, also played a role. Because the average distance between the target and (mean) distractor orientation was 90 in our design, this would likely still help the search (e.g., +30° would become 0°; −60° would become −90°).

Our findings also go against a recent neurocomputational model of autism based on divisive normalization, which predicted a reduced oblique effect in autism (see supplementary materials in Rosenberg et al., 2015). Rosenberg et al. (2015) used divisive normalization to qualitatively model existing findings and to predict new empirical findings in autism, assuming a decreased divisive (suppressive) normalization. However, contrary to the model, the oblique effect, as well as other perceptual effects based on divisive normalization (Palmer et al., 2018; Sandhu et al., 2020; Van de Cruys, Vanmarcke, Steyaert, & Wagemans, 2018), seem to be preserved in autism.

While studies in adults have shown that the variance of the distractor distribution can be learned in a limited number of trials (Chetverikov et al., 2016, 2017a, 2017c), our data in children suggests they cannot (yet) learn the precise width (variance) of a Gaussian distribution, and/or may rely on simpler heuristics such as the range. Specifically, Chetverikov et al. (2017a) showed that for neurotypical adults the difference between a normal and a uniform (range) type of distribution arises after 1 and 2 trials already. The fact that the CT-PD curves are flat within the full range of the normal distribution and only then decrease (see Figure 7) suggests that children are not really representing the distribution as a Gaussian. Of course, we cannot exclude that children may be able to implicitly learn more about the distribution given a lot more trials than the 5 and 6 we used.

We should emphasize that the comparison with adult data should be interpreted with some caution because of the differences in baseline response times (see Figure 7). Because increased response times or an increase in noise will only add noise or bias along the y-axis (independent of CT-PD values), they will not change the shape of the curve. However, a large change in the baseline response times may be indicative of a substantial difference in the way participants conduct the task, namely in a more serial, less efficient way. Indeed, at least in tasks that require the judgment of average location of sets of dots, children have been found to use less efficient and more variable sampling strategies (Jones et al., 2019; Jones & Dekker, 2018). Other studies confirm that averages can be extracted from very early in development (Manning et al., 2014; Sweeny et al., 2015), but children pooled over a lower number of items compared to adults. Such decreased sampling may explain the decreased precision of the encoding of the variance of the distractor distribution in children that we report. Our implicit measure of ensemble statistics also showed that the mean was implicitly learned in both our groups, consistent with earlier explicit tasks of summary statistics in children (and inconsistent with an overall global deficit in autism as hypothesized by Happé & Frith, 2006).

While the findings are consistent with an acquisition of a broader distribution than the one presented, implying that children form broader contextual priors than adults, such “weaker” priors are *not* limited to individuals with autism, as sometimes hypothesized (Pellicano & Burr, 2012). Only outside of the range of the distribution, the response times drop significantly, which could point to the encoding of the Gaussian distractor distribution as a uniform one (Chetverikov et al., 2017c) in children, that is, taking into account the range of the distribution only. Hence, our findings also do not align with an enhanced perceptual functioning account or the idea of increased sensory precision in ASD (Brock, 2012; Mottron et al., 2006; Van de Cruys et al., 2014), since those accounts would predict a sharper or in any case more accurate representation of the distribution in the ASD group.

In future work, it will be interesting to investigate why children with ASD lose their usual edge in visual search performance in our more complex task. Both the extent of spatial (and temporal) pooling (number of items), and the *weights* of the different items contributing to the mean and variance estimation might vary (Alvarez, 2011). In addition, it is sometimes hypothesized that the key problem in ASD may be in disentangling irrelevant (noise) variability from relevant dimensions of variability (Van de Cruys et al., 2017). Hence, adding an irrelevant dimension of variability (e.g., color) to the paradigm may be promising (Hansmann-Roth et al., 2019).

Finally and most importantly, a study with adults with ASD should verify whether the capacity to encode the precise distractor distribution can be acquired with aging, as seems to be the case for neurotypical adults, or whether autistic individuals are generally stuck with broader prior distributions. Adult participants would also allow us to increase the trial load and add conditions with different distribution types (Gaussian, uniform) and widths, as done in earlier studies using this paradigm in typical participants (e.g., Chetverikov et al., 2016, 2017a) in order to better characterize distribution learning in autism as well as dissociate possible effects of learning of the target distribution of priming trials versus learning (of the shape of) the distractor distribution. Indeed, the fact that, contrary to research in adults, we did not find a clear reproduction of the shape of the distractor distribution (i.e., monotonic decrease in RT corresponding to monotonic decrease in distractor probability density), leaves open a possible contribution of target distribution learning (in both groups).

In conclusion, we present the first evidence on feature distribution learning in children. Using our implicit measure, we show that the variance learned was much broader than the one of the presented distribution, consistent with less informative or broader priors in children irrespective of ASD diagnosis. This may point to a level of developmental maturation required to neurally represent precise distributions, as we see in adults. In contrast, structural priors (those that do not depend on learning within the task) do already have a strong effect on children's visual search performance, again irrespective of ASD diagnosis.

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## AUTHOR CONTRIBUTIONS

**Sander Van de Cruys:** Conceptualization, Design, Data Collection, Data Analysis, Visualization, Writing-Original draft preparation, Writing - Review & Editing; **Lisa Lemmens:** Conceptualization, Design, Data Collection, Data Analysis, Writing - Review & Editing; **Laurie-Anne Sapey-Triomphe:** Conceptualization, Design, Writing - Review & Editing; **Andrey Chetverikov:** Conceptualization, Design, Data analysis, Resources, Visualization, Writing - Review & Editing; **Ilse Noens:** Conceptualization, Design, Resources, Writing - Review & Editing; **Johan Wagemans:** Conceptualization, Design, Resources, Writing - Review & Editing, Funding acquisition.

## CONFLICT OF INTEREST

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

All code and data are available at osf.io/95672 (doi: 10.17605/OSF.IO/95672).

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## REFERENCES

Achenbach, T. M., & Ruffle, T. M. (2000). The child behavior checklist and related forms for assessing behavioral/emotional problems and competencies. *Pediatrics in Review/American Academy of Pediatrics*, *21*(8), 265–271. https://doi.org/10.1542/pir.21-8-265

Alvarez, G. A. (2011). Representing multiple objects as an ensemble enhances visual cognition. *Trends in Cognitive Sciences*, *15*(3), 122–131. https://doi.org/10.1016/j.tics.2011.01.003

American Psychiatric Association. (2000). Diagnostic and statistical manual, 4th edn, Text Revision (DSM-IV-TR).

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders (DSM-5®)*. American Psychiatric Pub.

Baldassi, S., Pei, F., Megna, N., Recupero, G., Viespoli, M., Igliozzi, R., Tancredi, R., Muratori, F., & Cioni, G. (2009). Search superiority in autism within, but not outside the crowding regime. *Vision Research*, *49*(16), 2151–2156. https://doi.org/10.1016/j.visres.2009.06.007

Brock, J. (2012). Alternative Bayesian accounts of autistic perception: Comment on {P}ellicano and {B}urr. *Trends in Cognitive Sciences*, *16*(12), 573–574; author reply: 574–575. https://doi.org/10.1016/j.tics.2012.10.005

Chetverikov, A., Campana, G., & Kristjánsson, Á. (2016). Building ensemble representations: How the shape of preceding distractor distributions affects visual search. *Cognition*, *153*, 196–210. https://doi.org/10.1016/j.cognition.2016.04.018

Chetverikov, A., Campana, G., & Kristjánsson, Á. (2017a). Rapid learning of visual ensembles. *Journal of Vision*, *17*(2), 21. https://doi.org/10.1167/17.2.21

Chetverikov, A., Campana, G., & Kristjánsson, Á. (2017b). Learning features in a complex and changing environment: A distribution-based framework for visual attention and vision in general. *Progress in Brain Research*, *236*, 97–120. https://doi.org/10.1016/bs.pbr.2017.07.001

Chetverikov, A., Campana, G., & Kristjánsson, Á. (2017c). Representing color ensembles. *Psychological Science*, *28*(10), 1510–1517. https://doi.org/10.1177/0956797617713787

Chetverikov, A., Campana, G., & Kristjánsson, Á. (2017d). Set size manipulations reveal the boundary conditions of perceptual ensemble learning. *Vision Research*, *140*, 144–156. https://doi.org/10.1016/j.visres.2017.08.003

Chetverikov, A., Hansmann-Roth, S., Tanrıkulu, Ö. D., & Kristjánsson, Á. (2020). Feature distribution learning (FDL): A new method for studying visual ensembles perception with priming of attention shifts. In S. Pollmann (Ed.), *Spatial learning and attention guidance* (pp. 37–57). Springer US. https://doi.org/10.1007/7657_2019_20

Cheung, C. H. M., Bedford, R., Johnson, M. H., Charman, T., Gliga, T., & BASIS team. (2018). Visual search performance in infants associates with later ASD diagnosis. *Developmental Cognitive Neuroscience*, *29*, 4–10. https://doi.org/10.1016/j.dcn.2016.09.003

Constant, A., Bervoets, J., Hens, K., & Van de Cruys, S. (2018). Precise worlds for certain minds: An ecological perspective on the relational self in autism. *Topoi. An International Review of Philosophy*, *39*, 1–12. https://doi.org/10.1007/s11245-018-9546-4

Corbett, J. E., Venuti, P., & Melcher, D. (2016). Perceptual averaging in individuals with autism Spectrum disorder. *Frontiers in Psychology*, *7*, 1735. https://doi.org/10.3389/fpsyg.2016.01735

Croydon, A., Karaminis, T., Neil, L., Burr, D., & Pellicano, E. (2017). The light-from-above prior is intact in autistic children. *Journal of Experimental Child Psychology*, *161*, 113–125. https://doi.org/10.1016/j.jecp.2017.04.005

Dickinson, A., Bruyns-Haylett, M., Smith, R., Jones, M., & Milne, E. (2016). Superior orientation discrimination and increased peak gamma frequency in autism spectrum conditions. *Journal of Abnormal Psychology*, *125*(3), 412–422. https://doi.org/10.1037/abn0000148

Dunn, W., & Rietman, A. (2006). *Sensory Profile-NL 3 t/m 10 jaar- - Handleiding*. Amersfoort: Studio Imago.

Friston, K., & Kiebel, S. (2009). Predictive coding under the free-energy principle. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *364*(1521), 1211–1221. https://doi.org/10.1098/rstb.2008.0300

Girshick, A. R., Landy, M. S., & Simoncelli, E. P. (2011). Cardinal rules: Visual orientation perception reflects knowledge of environmental statistics. *Nature Neuroscience*, *14*(7), 926–932. https://doi.org/10.1038/nn.2831

Gliga, T., Bedford, R., Charman, T., Johnson, M. H., & BASIS Team. (2015). Enhanced visual search in infancy predicts emerging autism symptoms. *Current Biology: CB*, *25*(13), 1727–1730. https://doi.org/10.1016/j.cub.2015.05.011

Gotham, K., Risi, S., Pickles, A., & Lord, C. (2007). The autism diagnostic observation schedule: Revised algorithms for improved diagnostic validity. *Journal of Autism and Developmental Disorders*, *37*(4), 613–627. https://doi.org/10.1007/s10803-006-0280-1

Haberman, J., & Whitney, D. (2012). Ensemble perception: Summarizing the scene and broadening the limits of visual processing. From Perception to Consciousness: Searching with Anne Treisman, 339–349.

Hansmann-Roth, S., Chetverikov, A., & Kristjánsson, Á. (2019). Representing color and orientation ensembles: Can observers learn multiple feature distributions? *Journal of Vision*, *19*(9), 2. https://doi.org/10.1167/19.9.2

Happé, F., & Frith, U. (2006). The weak coherence account: Detail-focused cognitive style in autism Spectrum disorders. *Journal of Autism and Developmental Disorders*, *36*(1), 5–25. https://doi.org/10.1007/s10803-005-0039-0

Hohwy, J. (2013). *The predictive mind*. Oxford University Press. http://books.google.be/books?id=3m8nAgAAQBAJ

Jones, P. R., & Dekker, T. M. (2018). The development of perceptual averaging: Learning what to do, not just how to do it. *Developmental Science*, *21*(3), e12584. https://doi.org/10.1111/desc.12584

Jones, P. R., Landin, L., McLean, A., Juni, M. Z., Maloney, L. T., Nardini, M., & Dekker, T. M. (2019). Efficient visual information sampling develops late in childhood. *Journal of Experimental Psychology. General*, *148*(7), 1138–1152. https://doi.org/10.1037/xge0000629

Kaldy, Z., Kraper, C., Carter, A. S., & Blaser, E. (2011). Toddlers with autism Spectrum disorder are more successful at visual search than typically developing toddlers. *Developmental Science*, *14*(5), 980–988. https://doi.org/10.1111/j.1467-7687.2011.01053.x

Karaminis, T., Neil, L., Manning, C., Turi, M., Fiorentini, C., Burr, D., & Pellicano, E. (2017). Ensemble perception of emotions in autistic and typical children and adolescents. *Developmental Cognitive Neuroscience*, *24*, 51–62. https://doi.org/10.1016/j.dcn.2017.01.005

Karvelis, P., Seitz, A. R., Lawrie, S. M., & Seriès, P. (2018). Autistic traits, but not schizotypy, predict increased weighting of sensory information in Bayesian visual integration. *eLife*, *7*, e34115. http://doi.org/10.7554/elife.34115.

Lai, M.-C., Lombardo, M. V., Auyeung, B., Chakrabarti, B., & Baron-Cohen, S. (2015). Sex/gender differences and autism: Setting the scene for future research. *Journal of the American Academy of Child and Adolescent Psychiatry*, *54*(1), 11–24. https://doi.org/10.1016/j.jaac.2014.10.003

Lawson, R. P., Mathys, C., & Rees, G. (2017). Adults with autism overestimate the volatility of the sensory environment. *Nature Neuroscience*, *20*(9), 1293–1299. https://doi.org/10.1038/nn.4615

Lawson, R. P., Rees, G., & Friston, K. J. (2014). An aberrant precision account of autism. *Frontiers in Human Neuroscience*, *8*, 302. https://doi.org/10.3389/fnhum.2014.00302

Lieder, I., Adam, V., Frenkel, O., Jaffe-Dax, S., Sahani, M., & Ahissar, M. (2019). Perceptual bias reveals slow-updating in autism and fast-forgetting in dyslexia. *Nature Neuroscience*, *22*(2), 256–264. https://doi.org/10.1038/s41593-018-0308-9

Manning, C., Dakin, S. C., Tibber, M. S., & Pellicano, E. (2014). Averaging, not internal noise, limits the development of coherent motion processing. *Developmental Cognitive Neuroscience*, *10*, 44–56. https://doi.org/10.1016/j.dcn.2014.07.004

Manning, C., Tibber, M. S., Charman, T., Dakin, S. C., & Pellicano, E. (2015). Enhanced integration of motion information in children with autism. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *35*(18), 6979–6986. https://doi.org/10.1523/JNEUROSCI.4645-14.2015

Manning, C., Tibber, M. S., & Dakin, S. C. (2017). Visual integration of direction and orientation information in autistic children. *Autism & Developmental Language Impairments*, *2*, 2396941517694626. https://doi.org/10.1177/2396941517694626

Mottron, L., Dawson, M., Soulières, I., Hubert, B., & Burack, J. (2006). Enhanced perceptual functioning in autism: An update, and eight principles of autistic perception. *Journal of Autism and Developmental Disorders*, *36*(1), 27–43. http://www.ncbi.nlm.nih.gov/pubmed/16453071

Norman, L. J., Heywood, C. A., & Kentridge, R. W. (2015). Direct encoding of orientation variance in the visual system. *Journal of Vision*, *15*(4), 3. https://doi.org/10.1167/15.4.3

Palmer, C. J., Lawson, R. P., & Hohwy, J. (2017). Bayesian approaches to autism: Towards volatility, action, and behavior. *Psychological Bulletin*, *143*(5), 521–542. https://doi.org/10.1037/bul0000097

Palmer, C. J., Lawson, R. P., Shankar, S., Clifford, C. W. G., & Rees, G. (2018). Autistic adults show preserved normalisation of sensory responses in gaze processing. *Cortex; A Journal Devoted to the Study of the Nervous System and Behavior*, *103*, 13–23. https://doi.org/10.1016/j.cortex.2018.02.005

Pellicano, E., & Burr, D. (2012). When the world becomes "too real": A Bayesian explanation of autistic perception. *Trends in Cognitive Sciences*, *16*(10), 504–510. https://doi.org/10.1016/j.tics.2012.08.009

Rhodes, G., Neumann, M. F., Ewing, L., & Palermo, R. (2015). Reduced set averaging of face identity in children and adolescents with autism. *Quarterly Journal of Experimental Psychology*, *68*(7), 1391–1403. https://doi.org/10.1080/17470218.2014.981554

Roeyers, H., Druart, C., De Schryver, M., & Schittekatte, M. (2011). *SRS Screeningslijst voor autismespectrumstoornissen*. Hogrefe.

Rosenberg, A., Patterson, J. S., & Angelaki, D. E. (2015). A computational perspective on autism. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(30), 9158–9165. https://doi.org/10.1073/pnas.1510583112

Rosenholtz, R. (2001). Visual search for orientation among heterogeneous distractors: Experimental results and implications for signal-detection theory models of search. *Journal of Experimental Psychology. Human Perception and Performance*, *27*(4), 985–999.

Sandhu, T. R., Rees, G., & Lawson, R. P. (2020). Preserved low-level visual gain control in autistic adults. *Wellcome Open Research*, *4*(208), 208.

Sapey-Triomphe, L.-A., Timmermans, L., & Wagemans, J. (2020). *Priors bias perceptual decisions in autism, but are less flexibly adjusted to the context*. Autism Research: Official Journal of the International Society for Autism Research.

Sattler, J. M. (2001). *Assessment of children: Cognitive applications* (p. 931). Jerome M. Sattler, Publisher. *Inc*.

Seriès, P., & Seitz, A. R. (2013). Learning what to expect (in visual perception). *Frontiers in Human Neuroscience*, *7*, 668. https://doi.org/10.3389/fnhum.2013.00668

Shafai, F., Armstrong, K., Iarocci, G., & Oruc, I. (2015). Visual orientation processing in autism spectrum disorder: No sign of enhanced early cortical function. *Journal of Vision*, *15*(15), 18. https://doi.org/10.1167/15.15.18

Solomon, J. A. (2010). Visual discrimination of orientation statistics in crowded and uncrowded arrays. *Journal of Vision*, *10*(14), 19. https://doi.org/10.1167/10.14.19

Sweeny, T. D., Wurnitsch, N., Gopnik, A., & Whitney, D. (2015). Ensemble perception of size in 4- -5-year-old children. *Developmental Science*, *18*(4), 556–568. https://onlinelibrary.wiley.com/doi/abs/10.1111/desc.12239

Sysoeva, O. V., Davletshina, M. A., Orekhova, E. V., Galuta, I. A., & Stroganova, T. A. (2015). Reduced oblique effect in children with autism spectrum disorders (ASD). *Frontiers in Neuroscience*, *9*, 512. https://doi.org/10.3389/fnins.2015.00512

Teufel, C., & Fletcher, P. C. (2020). Forms of prediction in the nervous system. *Nature Reviews. Neuroscience*, *21*(4), 231–242. https://doi.org/10.1038/s41583-020-0275-5

Van de Cruys, S., Evers, K., Van der Hallen, R., Van Eylen, L., Boets, B., de Wit, L., & Wagemans, J. (2014). Precise minds in uncertain worlds: Predictive coding in autism. *Psychological Review*, *121*(4), 649–675. https://doi.org/10.1037/a0037665

Van de Cruys, S., Van der Hallen, R., & Wagemans, J. (2017). Disentangling signal and noise in autism spectrum disorder. *Brain and Cognition*, *112*, 78–83. https://doi.org/10.1016/j.bandc.2016.08.004

Van de Cruys, S., Vanmarcke, S., Steyaert, J., & Wagemans, J. (2018). Intact perceptual bias in autism contradicts the decreased normalization model. *Scientific Reports*, *8*, 12559. https://doi.org/10.1038/s41598-018-31042-z

Van de Cruys, S., Vanmarcke, S., Van de Put, I., & Wagemans, J. (2018). The use of prior knowledge for perceptual inference is preserved in ASD. *Clinical Psychological Science*, *6*, 382–393. https://doi.org/10.1177/2167702617740955

Van der Hallen, R., Evers, K., Brewaeys, K., Van den Noortgate, W., & Wagemans, J. (2015). Global processing takes time: A meta-analysis on local-global visual processing in ASD. *Psychological Bulletin*, *141*(3), 549–573. https://doi.org/10.1037/bul0000004

Van der Hallen, R., Lemmens, L., Steyaert, J., Noens, I., & Wagemans, J. (2017). Ensemble perception in autism spectrum disorder: Member-identification versus mean-discrimination. *Autism Research: Official Journal of the International Society for Autism Research*, *10*(7), 1291–1299. http://onlinelibrary.wiley.com/doi/10.1002/aur.1767/full

Wechsler, D. (1992). *Wechsler intelligence scale for children (3rd Edition NL)*. The Psychological Corporation.

Whitney, D., Haberman, J., & Sweeny, T. D. (2014). *49 From Textures to Crowds: Multiple Levels of Summary Statistical Perception*.

Whitney, D., & Yamanashi Leib, A. (2018). Ensemble Perception. *Annual Review of Psychology*, *69*, 105–129. https://doi.org/10.1146/annurev-psych-010416-044232

Zaidel, A., Goin-Kochel, R. P., & Angelaki, D. E. (2015). Self-motion perception in autism is compromised by visual noise but integrated optimally across multiple senses. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(20), 6461–6466. https://doi.org/10.1073/pnas.1506582112

## SUPPORTING INFORMATION

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