Supplemental Online Material

Atypical visual motion prediction abilities in autism spectrum disorder

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S1. Extraction of the stimulus centroid

Given that our stimulus (a bird) was inherently asymmetric in its visual features (i.e., as compared to a circle), we used the centroid of the bird as the point that indicates its position. This was used to compute the actual response time relative to the target position. The centroid was obtained using the *regionprops* function in MATLAB that takes into account pixel intensities, and the result was centroid that was shifted 0.2° to the right from the image center.

S2. Eye movement analyses

The eye traces were classified into three types of eye movements: saccades, smooth pursuits, and fixations (Fig. 1B, left). To detect saccades, first, eye velocity traces were obtained through differentiation of eye position over time. Samples with velocity greater than 30°/s were categorized as saccades (a minimum of two consecutive samples that met this criterion was required). In addition, we only counted saccades whose amplitude was greater than 0.5°. Saccade amplitude was defined by the distance between the maximum and minimum position values across samples within a saccade period (Komogortsev & Karpov, 2013). Saccades were removed from the eye traces for smooth pursuit detection (Fig. 1B, right). Two samples before and after the detected saccades were also discarded. The excluded velocity samples were linearly interpolated. Velocity traces were then filtered using a low-pass, second-order Butterworth filter with cutoff frequency of 40 Hz.

We additionally implemented two exclusion criteria. First, to include the trials where participants closely tracked the object, we calculated the root-mean-square error (RMSE) between the eye and stimulus. Second, to ensure that saccade samples were correctly removed using our procedure, we obtained the SD in saccade-removed velocity traces. Then, we removed the top 2.5% of the trials (remaining after the removal of trials with eye blinks) with the highest values in each of the two measures (Smyrnis et al., 2007). Note that some trials met both of the criteria, thus resulting in discarding ~3.5% of the trials on average for each participant. Results do not change when including these trials.

To detect smooth pursuit eye movements, we first detected the pursuit onset by using a piecewise linear regression that estimated two line segments and a break point from the velocity trace (Spering, Dias, Sanchez, Schütz, & Javitt, 2013; Spering, Schütz, Braun, & Gegenfurtner, 2011). The break point indicated the pursuit onset. Visual inspection of the raw position data suggested that not all eye movements started at the dynamic circle that indicated the initial stimulus position. For instance, on some trials, participants first fixated at the assigned target location and then caught up with the moving stimulus. To account for this, we used a sliding window (300 ms each) from the beginning of the eye recording until the stimulus disappeared behind the occluder. This allowed us to avoid using an arbitrary window for detecting pursuit onset in a less controlled set up like ours. We performed the piecewise linear regression in each of these windows, and the average of the obtained break points was used as a pursuit onset. We only counted the break points where the difference between the slopes of the two estimated line segments was greater than 25% of the stimulus velocity. Despite the use of a less traditional method, mean pursuit onsets observed in our study are similar to those reported in previous studies (e.g., Spering et al., 2013).

We also employed a position dispersion criterion for detecting smooth pursuits versus fixations (Komogortsev & Karpov, 2013) using a similar sliding window analysis over the entire trace. Within each 100 ms window, we calculated the dispersion by taking the sum of absolute differences between the maximum and minimum position in both horizontal and vertical eye positions. If a sample was not marked as a saccade and the dispersion was greater than 1°, then it was counted as a pursuit. A trial was classified as a ‘pursuit trial’ if a pursuit onset was detected from the piecewise linear regression and the pursuit lasted more than five samples as determined by dispersion. If the dispersion was smaller than 1°, then the sample was counted as a fixation.

S3. Assessment of the quality of eye movement data

To evaluate the quality of eye movement data, we calculated the position root-mean square error (RMSE) for the analyzed trials, which quantifies the difference between the eye and object position. The mean position RMSE for the analyzed trials was 5.87° for ASD and 4.72° for TD ($t(34) = 1.44$, $p = .16$). The mean position RMSE during the closed-loop was 4.23° for ASD and 4.11° for TD ($t(34) = .15$ $p = .88$). The values are within the range of those reported in previous studies when considering the stimulus speeds (Takarae, Minshew, Luna, Krisky, & Sweeney, 2004) and the age range of our participants (Katsanis, Iacono, & Harris, 1998; Smyrnis et al., 2007; Takarae et al., 2004). In other words, our paradigm and measurements yielded data that are of sufficient quality and comparable to prior work.

Table S1. BIC values for the models in the analyses of closed pursuit gain predicting prediction performance

	Predictors	
	Closed-loop gain	Closed-loop gain, visible duration
ASD: Bias	-99.2	-96.86
ASD: Variability	-131.95	-120.15
TD: Bias	-124.37	-113.06
TD: Variability	-141.84	-129.78

S4. An ideal observer model of prediction bias

We constructed an ideal observer model to determine what optimal behavior looks like given our experimental settings. It was assumed that the ideal observer had complete knowledge of the occluded duration distribution, and the sensory noise linearly increased as the occluded duration increased. In other words, the ideal observer has full knowledge of stimulus statistics and its "perception" was limited by realistic sensory noise. The relation between the measured duration (t_m) and the physical duration (t) was formalized as,

$$t_m = t + \varepsilon ,$$

where ε followed a Gaussian distribution with zero mean and kt standard deviation. k represented Weber fraction. Given an occluded duration (t), we sampled 500,000 noisy measurements (t_m) and numerically computed the mean of posterior distribution for each measurement to compute the expected response of the ideal observer.

Figure S1 shows the mean bias curves of the ideal observer for four different Weber fractions (k = 0.01, 0.05, 0.1, 0.15). The size of bias increases as the Weber fraction increases. Notably, the bias curves for Weber fractions 1 and 1.5 closely resemble the empirical data we observed in block 4 (Fig. 2B). The Weber fraction of duration estimation reported in the literature is around one (Jazayeri & Shadlen, 2010).

The initial increase of the bias is due to the Weber's law. When the occluded duration is very short, the sensory noise is small, and the ideal observer does not strongly depend on the prior knowledge. As the occluded duration increases, the sensory noise increases following the Weber's law, and consequently, the ideal observer depends more on the prior knowledge, which increases the size of central tendency bias.

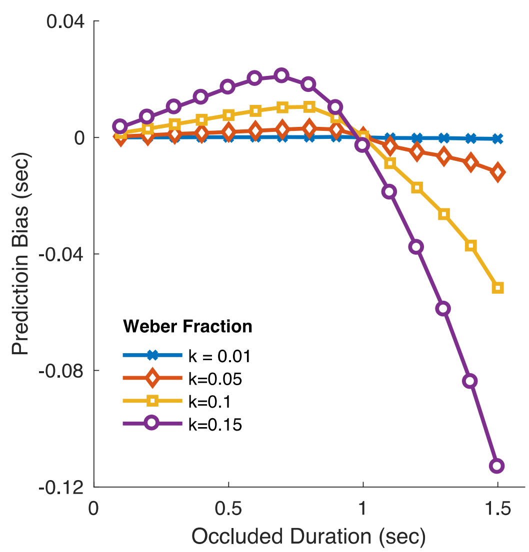

Figure S1. Prediction performance of the ideal observer model across varying occluded durations for four different Weber fractions. The size of bias increases as the Weber fraction increases. Overall pattern of the prediction bias of the ideal observer (k=0.1 and k=0.15) closely resembles the observed pattern of the prediction bias (Fig. 2A).

S5. The influence of impulsivity or subjective difficulty on early bias in ASD

We tested whether the differences in prediction bias between ASD and TD might have been due to other additional factors. First, we ruled out the possibility that this early bias in ASD was simply a result of impatience or impulsivity. Specifically, we examined the relationship between the early bias (as indexed by the bias in the longest duration time bin) and the raw impulsivity score from a clinical, parent-report measure. We did not find such a relationship ($r(17) = .22$, $p = .37$). Second, we also tested whether overall subjective difficulty or motivation may have differed in ASD across blocks, as well as between the first and last 50 trials within a block. We used prediction variability as an index for this test based on the reasoning that general difficulty or motivation would be related to non-random error. The results showed that prediction variability was not significantly different across blocks ($F(1.58, 69.32) = 1.45$, $p = .24$) nor between the first and last 50 trials in each block ($F(1, 44) = .06$, $p = .81$). These variables did not show significant interactions with group (all p's $> .20$).

S6. Group differences in pursuit gain without the outlier participant

Even after removing the outlier participant who showed the largest occluded pursuit gain, we found better smooth pursuit quality during occluded period in ASD. There was a significant interaction between pursuit period and group ($F(2, 66) = 11.37$, $p < .001$). Post hoc t-tests showed significantly smaller open gain ($t(33) = -2.61$, $p = .03$) and larger occluded gain ($t(26.61) = 2.1$, $p = .045$) in ASD than in TD. There was no group difference in closed gain ($t(33) = .25$, $p = .81$).

S7. Relationship between occluded pursuit gain and prediction performance

We did not observe a significant difference in the average occluded pursuit gain across visible durations ($F(1, 34) =.77$, $p = .39$). However, the linear mixed effects model analyses, testing whether occluded pursuit gain predicted prediction bias or variability in each group, revealed a pattern in ASD that is consistent with those using the closed-loop pursuit gain (shown in Figs. 4B & C in the main text). Better pursuit during occluded period was related to reduced prediction variability in TD, although the effect did not reach significance ($\beta_{gain} = -.14$, $SE = .07$,

$t(26.64) = -1.96$, $p =. 06$). In ASD, occluded pursuit gain significantly predicted prediction bias, with better pursuit during the occluded period with greater early bias ($\beta_{gain} = -.10$, $SE = .05$, $t(17.12) = -2.29$, $p = .04$). There was no significant relationship between occluded gain and prediction bias in TD ($\beta_{gain} = .07$, $SE = .08$, $t(26.12) = .88$, $p = .39$), and between occluded gain and variability in ASD ($\beta_{gain} = .02$, $SE = .04$, $t(19.67) = .54$, $p = .59$). The BIC values in all models were lower compared to those with the visible duration as a predictor (see Table S2 below). The exception was the one testing the relationship between occluded gain and prediction bias in ASD, which had a higher BIC value than the model with the visible duration as a predictor. Nevertheless, the occluded pursuit gain significantly predicted prediction bias in ASD even in this model ($\beta_{gain} = -.11$, $SE = .04$, $t(17.78) = -2.56$, $p = .02$; $\beta_{VisDur} = .04$, $SE = .01$, $t(17.25) = 3.93$, $p = .001$).

Table S2. BIC values for the models in the analyses of occluded pursuit gain predicting prediction performance

	Predictors	
	Occluded-period gain	Occluded-period gain, visible duration
ASD: Bias	-100.31	-100.99
ASD: Variability	-130.94	-119.39
TD: Bias	-127.18	-115.77
TD: Variability	-132.48	-126.28

S8. Performance across different types of eye movement trials

Because several of the key analyses reported in this paper were performed only using the "pursuit trials" (i.e., trials where participants showed a smooth pursuit behavior), it is important to ensure that this trial selection did not bias the stimulus characteristics and/or obscure potentially important group differences in prediction performance. Thus, we examined the differences in stimulus characteristics as well as the prediction performance in three differently categorized trial types: pursuit trials, no-pursuit trials, and unused trials that were eliminated due to missing samples (e.g., eye blinks; see *Eye movement analysis* section of the *Methods*).

First, we found stimulus differences that were consistent with how trial types were derived. The classified trials varied in the visible ($F(2, 68) = 110.95$, $p < .001$) and occluded durations ($F(2, 68) = 162.63$, $p < .001$). Specifically, the unused trials had significantly longer visible (*mean* = .94 s, *SD* = .057) and occluded (*mean* = .87 s, *SD* = .097) durations compared to pursuit (all *p*'s < .03) and no-pursuit trials (all *p*'s < .001). This simply reflects the intuitive observation that participants were more likely to make eye blinks when the overall trial duration was longer. No-pursuit trials had significantly shorter visible (*mean* = .8 s, *SD* = .052) and occluded (*mean* = .55 s, *SD* = .084) durations than the pursuit trials (all *p*'s < .001). The mean visible and occluded durations for the pursuit trials were .92 s (*SD* = .034) and .74 s (*SD* = .056), respectively. This is consistent with our observation that the pursuit quality is worse for shorter visible duration and may even suggest that pursuit might have been difficult to execute when stimulus duration was too short.

Second, we tested if the prediction performance varied across trial types. For prediction bias, there was a significant main effect of trial type ($F(2, 68) = 7.05$, $p = .002$). However, this was mainly due to the difference between no-pursuit and unused trials ($p = .006$), with an earlier bias in no-pursuit trials (no-pursuit: *mean* = .95, *SD* = .046; unused: *mean* = .97, *SD* = .041). The prediction bias in pursuit trials—which were the focus of our main analyses—was not statistically different from the other two trial types (all *p*'s > .06; *mean* = .96, *SD* = .031). There was also a main effect of trial type on prediction variability ($F(1.64, 55.75) = 33.9$, $p < .001$), where the variability was largest for no-pursuit trials (*mean* = .2, *SD* = .053) compared to the other two trial types (all *p*'s < .001; pursuit: *mean* = .17, *SD* = .041; unused: *mean* = .17, *SD* = .047). These results potentially suggest that participants benefited from smooth pursuit. However, given that the overall trial duration was shorter for no-pursuit trials, this suggestion warrants further study with more explicit control of eye movements and comparable stimulus conditions (Makin & Poliakoff, 2011).

Most importantly, for our main interest, none of the analyses reported above were linked to group differences. We found no significant group differences in (all *p*'s > .12) nor interactions with group (all *p*'s > .10). This indicates that the differences in eye movements and resulting trial type classification similarly affected both ASD and TD.

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