Article:

Pirrone, A., Dickinson, A., Gomez, R. et al. (2 more authors) (2017) Understanding Perceptual Judgment in Autism Spectrum Disorder Using the Drift Diffusion Model. Neuropsychology, 31 (2). pp. 176-180. ISSN 0894-4105

https://doi.org/10.1037/neu0000320

Accepted text of: Pirrone, A., Dickinson, A., Gomez, R., Stafford, T. and Milne, E. (in press). Understanding perceptual judgement in autism spectrum disorder using the drift diffusion model. *Neuropsychology*.

Understanding Perceptual Judgement in Autism Spectrum Disorder using the Drift Diffusion Model

Angelo Pirrone, Abigail Dickinson, Rosanna Gomez, Tom Stafford, Elizabeth Milne

The University of Sheffield

Author Note

Angelo Pirrone, Department of Psychology and Department of Computer Science, Sheffield University. Abigail Dickinson, Department of Psychology, Sheffield University. Rosanna Gomez, Department of Psychology, Sheffield University. Tom Stafford, Department of Psychology, Sheffield University. Elizabeth Milne, Department of Psychology, Sheffield University.

We sincerely thank all of the participants who generously volunteered their time to take part in this study. We would also like to thank Dr Richard Smith for his previous assistance with participant recruitment.

Correspondence concerning this article should be addressed to Angelo Pirrone or Abigail Dickinson, Department of Psychology, Sheffield University, Western Bank, Sheffield, S10 2TN, UK. Contact: Apirrone1@sheffield.ac.uk or Abbydickinson317@gmail.com

Abstract

Objective: Two-alternative forced-choice tasks are widely used to gain insight into specific areas of enhancement or impairment in individuals with autism spectrum disorder (ASD). Data arising from these tasks have been used to support myriad theories regarding the integrity, or otherwise, of particular brain areas or cognitive processes in ASD. The drift diffusion model (DDM) provides an account of the underlying processes which give rise to accuracy and reaction time distributions, and parameterises these processes in terms which have direct psychological interpretation. Importantly, the DDM provides further insight into the origin of potential group differences in task performance. Here, for the first time, we used the DDM to investigate perceptual decision making in ASD.

Method: Adults with (N = 25) and without ASD (N = 32) performed an orientation discrimination task. A drift diffusion model was applied to the full RT distributions.

Results: Participants with ASD responded more slowly than controls, the groups did not differ in accuracy. Modelled parameters indicated that: (i) participants with ASD were more cautious than controls (wider boundary separation); (ii) non-decision time was increased in ASD; and (iii) the quality of evidence extracted from the stimulus (drift rate) did not vary between groups.

Conclusions: Taking the behavioural data in isolation would suggest reduced perceptual sensitivity in ASD. However, DDM results indicated that despite response slowing, there was no evidence of differential perceptual sensitivity between participants with and without ASD. Future use of the DDM in investigations of perception and cognition in ASD is highly recommended.

Keywords: autism; perception; drift diffusion model; 2AFC; orientation discrimination

Understanding Perceptual Judgement in Autism Spectrum Disorder using the Drift Diffusion Model

Autism Spectrum Disorder (ASD) is a heterogeneous neuropsychiatric disorder that affects social interaction and communication, and is associated with behavioural inflexibility and repetitive motor and sensory action. A large literature also highlights cognitive and perceptual anomalies in ASD, which under some conditions manifest as impairments, and under other conditions manifest as enhancements. For example, in the perceptual domain, individuals with ASD show impaired motion discrimination (Bertone, Mottron, Jelenic & Faubert, 2010; Milne et al. 2002), impaired facial matching (Deruelle, Rondan, Gepner & Tardif, 2004), enhanced discrimination of second-order motion (Bertone et al. 2010) enhanced visual search (O'Riordan, Plaisted, Driver & Baron-Cohen, 2001) and enhanced orientation discrimination (Dickinson, Bruyns-Haylett, Smith, Jones, & Milne, 2016). These discrete areas of strength and weakness have provided evidence for a number of prominent theories regarding the neruopathology of ASD including evidence for dorsal stream impairment (Pellicano, Gibson, Maybery, Durkin & Badcock, 2005; Deruelle et al. 2004), increased neural noise (Simmons et al. 2009), hypo-priors (Pellicano & Burr, 2012), and altered balance in the excitation to inhibition ratio in ASD (Dickinson et al. 2016).

The majority of studies that measure perception and cognition in ASD (including those cited above) utilise the popular two-alternative forced choice (2AFC) method whereby participants must make a judgment about a presented stimulus, such as "which way is the stimulus moving?" or "is a target present or absent?" Enhancement or impairment within a particular domain is then inferred from accuracy rates and / or response times. However, there are limitations to the conclusions that can be drawn by analysing response times and accuracy rates, as there are a number of processes that underlie a behavioural response in addition to the particular perceptual domain or cognitive skill that the task is designed to measure. These include response caution, response bias, and non-decision time (see White, Ratcliff, Vasey & McKoon, 2010). This is especially true in psychophysics tasks, where accuracy of response is usually the only dependent variable considered. Assume, for example, that participants with ASD prioritise accuracy over speed, while neurotypical individuals prioritise speed over accuracy. In this scenario the two groups could have identical perceptual sensitivities but would produce different accuracy functions. Similarly, if response time is the only dependent variable, then participants with ASD would appear to have a perceptual deficit when in fact they are simply exercising more caution when responding. These examples highlight that any finding based on a comparison between groups where one group shows greater accuracy than the other, or where one group shows slower performance than the other may be due to different speed/accuracy trade-offs (Heitz, 2014; Pachella, 1974; Palmer, Huk and Shadlen, 2005; Stone, 2014, Wickelgreen, 1977). It therefore becomes a priority to combine measures of speed and accuracy in order to get an accurate measure of perceptual sensitivity, as any claims of differences in perceptual sensitivity between groups which are based solely on accuracy measurements may be confounded.

Different methods for combining the analysis of speed and accuracy exist, but these typically make the assumption that speed and accuracy are linearly related (Seli, Jonker, Cheyne, & Smilek, 2013), an assumption which is particularly vulnerable if participants are performing at high levels of accuracy or near their asymptotic reaction time. A common method is to calculate an ‘efficiency’ score (speed/accuracy; Townsend and Ashby, 1982). However, the originators of this method explicitly recommended that this efficiency score should not be used in the case of speed-accuracy trade-offs, and subsequent investigation has shown that this measure can obscure group differences as easily as reveal them (Bruyer and Brysbaert, 2011). Fortunately, it is possible to perform a principled reconciliation of speed and accuracy information, via an explicit model of decision making called the Drift Diffusion Model (DDM, Ratcliff, 1978; Ratcliff and McKoon, 2008).

The DDM is a member of a class of decision making model called accumulator models, in which individual decisions are assumed to be made by a process which accumulates momentary evidence in favour of a decision towards some threshold for responding. This model provides an account of the underlying processes which produce both accuracy and reaction time results across different experimental conditions, and parameterises this process in terms which have a direct psychological interpretation: drift rate, boundary separation and non-decision time (see Figure 1). Drift rate reflects the strength of evidence for a judgement. Drift rates will vary with task, such that easier tasks produce higher drift rates, and with individual, such that participants with greater perceptual sensitivity also have higher drift rates. Boundary separation reflects the particular speed-accuracy trade-off that a participant maintains, i.e. their conservativeness when responding. Non-decision time reflects processes that are not directly related to the perceptual judgement such as encoding and motor preparation.

The DDM has been used in previous research to provide more accurate conclusions in studies investigating perception and cognition in clinical samples. For example, revealing that individuals with ADHD show inefficient information processing rather than impulsive information processing (Karalunas, Huang-Pollock & Nigg 2012; Metin et al. 2013). In addition, in a study of older adults (aged 60 and above), an apparent impairment in lexical decision making was shown to be accounted for by longer non-decision time and wider boundary separation (increased caution) and not by a difference in the quality of information extracted from the stimulus (drift-rate, Ratcliff, Thapar and McKoon, 2006). Thus using the

DDM to decompose behavioural data into behavioural components provided more precise conclusions regarding age-related changes in cognition.

Here, we used the DDM to provide a principled reconciliation of the speed and accuracy of perceptual decision making in individuals with and without ASD within a common decision making framework. To the best of our knowledge this study is the first to apply the DDM to perceptual judgments in ASD.

Method

Participants

Participants included 28 individuals with ASD (7 females) and 32 neurotypical (NT) volunteers (11 females) who were matched on age and non-verbal IQ using the matrix reasoning subtest of the WASI (Wechsler, 1999, see table 1 for participant details). All participants with ASD had received an independent diagnosis of ASD based on either DSM or ICD criteria from an experienced clinician working within the National Health Service in the UK prior to being recruited into the study. Exclusion criteria for all participants included history of epilepsy, migraine or seizure. Further exclusion criteria for the control group included having, or having been referred for a diagnosis of ASD, or having a first degree relative with ASD. Data from three participants with ASD were excluded as one participant did not complete the task, and two performed at chance level. Data from the remaining 57 participants (25 ASD, 32 NT) are reported below. Within the ASD sample, 22 participants had a diagnosis of Asperger’s syndrome, and three had a diagnosis of autism. Two participants with ASD had an additional diagnosis of ADHD and one had an additional diagnosis of OCD. Eleven participants with ASD and two NT participants were taking medication at the time of the study. Running analyses with and without these participants indicated that the effect of retaining participants who were taking medication was that both accuracy and response time slightly decreased in the ASD group. However, the significance of the DDM parameters did not change when these participants were excluded therefore the analyses reported below are based on data from individuals regardless of medication status. Some of the participants (17 with ASD and 9 NT controls) had taken part in our previous study measuring orientation discrimination (Dickinson et al., 2016).

In order to evaluate autism symptomatology, the participants with ASD completed module four of the Autism Diagnostic Observation Schedule (ADOS; Rutter, DiLavore, Risi, Gotham & Bishop, 2002, data were not obtained from one participant). The ADOS involves a semi-structured assessment which is designed to elicit specific social and communicative behaviours. Scores are based on the presence or absence of these behaviours. A score of 7 or above on the combined communication and interaction subscales is defined as the clinical cut-off for autism spectrum. Of the 24 participants who completed the ADOS, four did not meet the cut off for autism spectrum, obtaining scores of 2, 3, 4 & 5 respectively. Although some of these scores are low, we decided to retain these participants in the analysis as they all had a clinical diagnosis of ASD, and they scored above the clinical cut-off for ASD on the SRS-2 (see below, obtaining T-scores of 77, 70 and 63), or the Autism Spectrum Quotient (AQ[1], obtaining a score of 37).

The adult self-report version of the social responsiveness scale (SRS-2; Constantino & Gruber 2012) was used to assess social interaction and communication in both groups of participants (four of the participants with ASD and four of the NT controls did not complete the questionnaire). Higher scores indicate a greater severity of social impairment and ASD symptomology, with a T-score of 60 or above indicating clinically significant deficiencies in reciprocal social behaviour. Four participants in the NT group obtained SRS T-scores of either 60 or above. However, as these participants did not have a diagnosis of ASD, their data were retained in all analyses. One participant in the NT group did obtain a very high SRS score - 81which is considered to be in the severe range. Data were re-analysed after excluding this participant and the significance of results reported below did not change. Therefore as this participant did not have a diagnosis of ASD, his data were also retained in the analyses. The study received ethical approval from the local research ethics committee. Participants provided informed written consent, in accordance with the declaration of Helsinki.

Insert Table 1 about here please

Task, Stimuli and Apparatus

A two-alternative forced choice orientation discrimination task was used to measure perceptual decision making. Each trial began with the presentation of a central fixation cross which remained on screen for 500ms. This was followed by the appearance of two Gabor patches (99% contrast Gaussian-windowed sinusoidal gratings; 2.5 cycles per degree) presented on either side of the central fixation cross, on a mean luminance background (mean luminance 80 cd/m2). On each trial, the Gabor patch presented to the left of fixation was a reference stimulus which was always oriented at 45 degrees. The Gabor patch presented to the right of fixation was always the target. Participants were asked to judge, via a 2AFC button press using two fingers of their right hand, whether the Gabor patch on the right had been tilted clockwise, or anticlockwise compared to the reference stimulus. The Gabor patches remained on-screen until the participant made a response.

The task had a 2 x 5 design, with one factor of rotation (clockwise or anticlockwise) and another factor of degree of difference between the reference and the target grating (3°, 5°, 7°, 9°, 11°). Each condition consisted of 50 trials, resulting in a total of 500 trials which were randomly interleaved. Two practise trials were completed before the experimental trials began and participants had a short self-timed break after 250 trials. Stimuli were created in MatLab (The Mathworks, 2000) using the PsychToolbox set of functions (Brainard, 1997). Stimuli were displayed on a linearised Acer aspire S3 laptop screen, with a spatial resolution of 1366 x 768 pixels and a temporal resolution of 60Hz.

Results

Observed variables

For both the behavioural analyses and the model fitting we cleaned the data by excluding responses faster than 300 ms and slower than 3000 ms, removing in this way 9% of the data. Such cut-offs are based on existing literature (Ratcliff, Thapar and McKoon, 2006) suggesting that RTs below 300 ms are likely to be fast guesses while RTs above 3000 ms are likely to be attentional lapses, hence are not produced by a DDM one-shot decision process (Ratcliff, Thapar and McKoon, 2006).

Of *a priori* interest were the main effects of participant group (ASD vs NT) and stimulus angle (11°, 9°, 7°, 5° and 3°). Preliminary data visualisation also revealed a systematic difference between conditions where the target was rotated clockwise with respect to the reference stimulus compared to conditions where the target was rotated anticlockwise with respect to the reference stimulus. For this reason the analysis we present here uses group (ASD vs NT), rotation (clockwise / anticlockwise) and degree of difference (angle) as predictors with a linear regression model containing these three factors and all interactions (implemented in R, R Core Team, 2016). We analysed both observed variables and model parameters with this same model for ease of comparison.

In Figure 2 we show the effect of target stimulus properties (rotation and angle) on judgement accuracy and speed of correct judgements for the two groups. As expected there was a strong effect of angle on both measures: accuracy, $B = 0.032$, t=3.996, p<0.001; reaction time B=-0.065, t=-2.836, p<0.005. There was a large effect of participant group on reaction time, B=-0.366, t=-3.454, p<0.001, but not on accuracy, B=0.023, t=0.612, p=0.541. Additionally, there was an effect of rotation on accuracy, B=0.412, t=4.754, p<0.001, whereby responses were more accurate for the clockwise conditions compared to the anticlockwise conditions. Further, there was an interaction between rotation and group, B=-0.137, t=-2.582, p=0.010, as this effect was exaggerated for the ASD group, so much so that the accuracy of the ASD group was typically better than the NT group in the clockwise conditions and typically worse in the anticlockwise conditions. There was no significant effect of rotation on reaction time, B=-0.293, t=-1.195, p=0.233, nor was there a significant interaction between rotation and group B=0.140, t=0.937, p=0.349.

This complex pattern, in that certain factors significantly affect speed, but not accuracy, and vice versa, is a first suggestion that a correct account of differences in perceptual sensitivity between individuals with and without ASD may require combining both speed and accuracy information rather than comparing them separately.

Insert Figure 2 about here please

Model Fitting

We fitted the Drift Diffusion Model (Ratcliff, 1978; Ratcliff & McKoon, 2008) to the responses, taking into account both accuracy and speed (of both correct and incorrect responses). For estimating the parameters of the DDM we used EZ, a method proposed and made freely available by Wagenmakers, Van Der Maas & Grasman (2007). In Wagenmakers et al. (2007), the authors considered an unbiased DDM without variabilities in drift rate and non-decision time. This reduced and simplified version of the DDM allowed the authors to overcome the complexity of the parameter-fitting procedure (Ratcliff and Tuerlinckx, 2002) and to derive three simple equations that take mean correct response time, variance of correct response and response accuracy as input and produce drift rate, boundary separation and non-decision time as outputs. This method is particularly useful for estimating parameters in datasets with a relatively small number of trials or datasets containing few errors as was the case here.

In the EZ-estimation, we estimated the parameters for each participant and for each condition separately. Since the EZ-estimation does not work if accuracy is at ceiling, meaning that $P_c=1$, we employed a correction, replacing Pc with a value that corresponds to one error so that $P_c=1 -1/n$ where n is the total number of trials for each condition. We reasoned that since subjects are presented with conditions of different difficulty in a random order, they cannot adjust their criterion for a response before each trial is presented and for this reason for the two groups we computed an average boundary separation. At the same time, for each group, we computed a mean non-decision time component based on the average non-decision time component of each condition for each subject.

The parameter values, averaged over all individuals in each group, are plotted against judgement difficulty in Figure 3. Our primary interest was in the drift (see Figure 3A), which reflects participants' sensitivity to the stimuli. Using the same regression model as we used for the observed variables, we can see that the drift does not differ significantly by group, B=0.002, t=-0.086, p=0.932), but does, as we might expect, by degree of difference between the reference and the target stimulus (angle), B=0.009, t=2.372, p=0.018, and between clockwise and anticlockwise rotation, B=0.117, t=2.836, p<0.005. None of the interactions between predictors were significant (for the effect of group * rotation on drift, *B*= 0.003, *t*=1.460-, *p*=0.145).

Insert Figure 3 about here please

There were significant main effects of group on non-decision time, *B*=0.230, *t*=-3.797, *p*<0.001, but not on boundary separation, *B*=-0.012, *t*=-0.881, *p*=0.379. Recall that although we fitted each condition separately, a single parameter was chosen for the boundary separation and non-decision time (i.e. varying only by group), by averaging these across individuals, based on the logic that these parameters of a decision could not be altered in advance of the stimulus being known. If we fit the non-decision time and boundary parameters for each individual using a regression with group as the only predictor, then this factor is significant for both parameters: non-decision time, *B* = -0.121, *t*=-5.377, *p*<0.001; boundary, *B* = -0.019, *t*=-5.351, *p*<0.001. These data are shown in Figures 3B and 3C.

To demonstrate the goodness of fit of the model average boundary separation values and non-decision times from both groups were chosen as parameters (since differences in these parameters were not systematic across difficulty but there was a difference across groups) and the drift was averaged across individuals for each condition, then comparable data was generated in all experimental conditions by simulating 10000 trials for the each condition. Figure 4 shows comparisons of correct RTs and accuracy between the model and the observed data. For both groups, the model can be seen to fit the data very well.

In order to check whether it was reasonable to assume the decision process to be unbiased we investigated the difference between mean correct RTs and wrong RTs since the signature for a biased decision is in the difference between the speed of correct and wrong RT distributions for the two alternatives. In particular, if the decision-maker starts to integrate evidence near one of the two boundaries, fast RTs for that boundary and slow RTs for the opposite boundary are predicted. An inspection of the plots showed that in our case the relative speed of correct and wrong RTs did not differ systematically for different stimulus categories. However, given the very low number of observations for error responses (4 per conditions which decreases to 2.5 if +3 and -3 degrees are excluded) caution is needed when interpreting the speed of wrong responses that could be disproportionately influenced by few individuals with lower accuracy.

Insert Figure 4 about here please

Discussion

Here, using the drift diffusion model (Ratcliff, 1978; Ratcliff & McKoon, 2008), we have modelled the processes underlying perceptual decision making in ASD. Participants with and without ASD indicated whether a target grating was oriented clockwise or anticlockwise with respect to a reference grating tilted at 45^0. The results indicate that: (i) participants with ASD were more cautious than controls when responding, i.e. more likely to generate slow but accurate responses (wider boundary separation); and (ii) processes that are not directly related to the perceptual decision such as encoding or response execution take longer in individuals with ASD (increased non-decision time). The fact that there were no group differences in drift rate suggests that the quality of evidence extracted from the stimuli did not vary between groups.

Assuming that this finding of wider boundary separation and increased non-decision time in individuals with ASD extends to judgements other than discriminating angle of tilt, these findings have important implications for studies that use 2AFC choice methods to investigate perception and cognition in ASD. For example, increased response time in such paradigms is usually interpreted as cognitive or perceptual impairment, however the data reported here indicate that increased caution in responding and / or increased non-decision processes may underlie increased response time rather than a perceptual or cognitive deficit per se.

To the best of our knowledge, this is the first study to report the parameters of drift-rate, boundary separation and non-decision time in individuals with ASD. There are a handful of studies that have investigated these parameters in ADHD, with the general finding that individuals with ADHD have decreased drift-rate, decreased non-decision time and no difference in boundary separation compared to controls (see Karalunas, Geurts, Konrad, Bender & Nigg, 2012 for review). There is significant overlap between the occurrence of ASD and ADHD (Polderman, Hoekstra, Posthuma, & Larsson), and also in the cognitive profile of the two conditions (Geurts et al. 2008). Therefore, the clear differences in the parameters modelled here between previous data from individuals with ADHD and our current data obtained from people with ASD may provide a useful foundation from which to further understand the specific cognitive components that are affected in the two disorders, and the way in which the underlying neuropathology of the two conditions differs.

Previous work has found superior orientation discrimination in individuals with ASD (Dickinson et al. 2016). In contrast to the current work, this study employed an adaptive staircase which converged on 79% correct to measure perceptual thresholds (Dickinson et al. 2016). Therefore, in order to facilitate comparison between this previous study and the data reported here, psychometric functions were fitted to the accuracy data obtained from each participant with the aim of identifying each participant’s discrimination sensitivity at 79%.

However, in many cases, particularly for clockwise judgments, accuracy was too high for the psychometric function to reach 79% correct. This was the case for 88% of the ASD group and 64.5% of the NT group, providing partial support for the previous claim that orientation discrimination is superior in individuals with ASD. However, the fact that drift rate did not differ between the participants with and without ASD suggests that the extraction of visual information from the stimulus does not differ in individuals with ASD. Rather, group differences in orientation discrimination reported previously could be explained by other parameters such as increased caution when responding. However it is possible that had the task used here been more difficult for the participants, i.e. had we presented orientation differences lower than 3°, then differences in drift rate may have emerged (see figure 3A which shows drift rate is actually higher in the ASD group than the NT group in the most difficult condition). Further work, utilising a more sensitive task is required to confirm or refute this suggestion.

A limitation of this study is that the number of trials administered in each condition (50) was low, and the number of errors made was also low. For this reason we employed the EZ method which is more suitable for datasets with low numbers of trials. Figure 4 illustrates that the fit between the observed variables and modelled parameters was very good which confirmed our choice of method for modelling the data. However, the use of the EZ method in itself poses further limitations as it assumes that the decision is unbiased, and does not allow parameters to be constrained across conditions. In addition, the low number of trials does not allow a principled statistical test for the unbiasedness of the decision process. A later version of the EZ-estimation, EZ2 (Grasman, Wagenmakers and van der Maas, 2009), allows for the estimation of bias, however it only works if the proportion of correct is not 1 and has been shown to result in poor fits when drift rates are very high and number of errors are very low, and was therefore not applied here. For this reason we combined the trials from all participants with ASD and all NT participants to generate two ‘super-observers’ by considering the pooled datasets (i.e., all trials from all participants put together) for the two groups. Note that a quantile average fitting procedure has been proposed by some authors (e.g., Jiang, Rouder and Speckman, 2004). In this procedure the quantiles for each subject are calculated and then averaged across subjects to form a super-subject on which quantile fitting is performed. However, given the low number of error responses in our dataset, calculating quantile RTs would be problematic and we chose to fit the pooled datasets; thereby overcoming the problem of having a small number of trials per condition and a low error rate, and enabling us to estimate the full RT distributions of correct and incorrect responses for each condition.

For fitting the full DDM we used the Diffusion Model Analysis Toolbox (Vandekerckhove and Tuerlinckx, 2008) where we chose to estimate parameters using a maximum likelihood estimation method of the data grouped in quantiles that divide the RT distributions (the .1, .3,.5,.7 and .9 quantiles); also here, boundary and non-decision time were still allowed to vary by condition and we also allowed the starting point to vary by condition while across-trials variabilities were kept fixed for the two groups. In the fitting, the lower boundary represented the threshold for an ‘anti-clockwise’ decision while the upper boundary represented the threshold for a ‘clockwise’ decision. We ran the full DDM using DMAT on these super-observers, and replicated the results of increased boundary separation, increased non-decision time and no difference in drift-rate, reassuring us that the findings from this study are reliable despite the low trial rate.

Furthermore, given the low number of practice trials, it is conceivable that estimates of RT and variance would be influenced by initial trials during which subjects are learning the task. To check for this, we repeated our analyses using only the second half of trials. No change was observable from plotting the parameter estimates and model simulation compared to our main analyses (for the sake of brevity this analysis is not shown).

As can be seen in Figures 2, and 3A, responses were faster and more accurate and drift rate was higher when the target stimulus was tilted clockwise rather than anti-clockwise. This response bias could be explained by a number of factors, including a Simon effect given that the target grating always appeared to the right of the reference grating, or a bias towards responding clockwise rather than anti-clockwise. The significant interaction between group and stimulus rotation on accuracy (see Figure 2A) indicates that this response bias is exaggerated in participants with ASD. However, stimulus rotation did not interact with any of the other factors in the paradigm, and no significant group x rotation interaction effects were seen in the parameters generated by the DDM, therefore the main conclusions of the study, i.e. increased boundary separation, increased non-decision time and no difference in drift rate between individuals with and without ASD, are unaffected by this potential response bias. Nevertheless, future studies should avoid using paradigms in which the position of the target stimulus interacts with response category.

In sum, these data provide the first direct evidence for increased non-decision time and wider boundary separation in individuals with ASD, and therefore demonstrates that two non-perceptual parameters underlying perceptual decision making are altered in ASD compared to controls. This finding is likely to have fundamental consequences for the interpretation of data based on the 2AFC method in this population. Future work, employing the full version of the DDM (Ratcliff & McKoon, 2008), and across different types of decisions, is clearly warranted.

References

Bertone, A., Mottron, L., Jelenic, P., & Faubert, J. (2003). Motion perception in autism: a "complex" issue. *Journal of Cognitive Neuroscience, 15*(2), 218-225. doi:10.1162/089892903321208150

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial vision*, 10, 433-436. doi:10.1163/156856897X00357

Bruyer, R., & Brysbaert, M. (2011). Combining speed and accuracy in cognitive psychology: Is the inverse efficiency score (IES) a better dependent variable than the mean reaction time (RT) and the percentage of errors (PE)? *Psychologica Belgica*, 51(1), 5. http://hdl.handle.net/1854/LU-2001824

Constantino JN and Gruber CP. Social Responsiveness Scale Second Edition (SRS-2) Los Angeles: Western Psychological Services; 2012.

Deruelle, C., Rondan, C., Gepner, B., & Tardif, C. (2004). Spatial frequency and face processing in children with autism and Asperger syndrome. *Journal of autism and developmental disorders*, *34*(2), 199-210. doi:10.1023/B:JADD.0000022610.09668.4c

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. doi:10.1037/abn0000148

Geurts, H. M., Grasman, R. P., Verté, S., Oosterlaan, J., Roeyers, H., van Kammen, S. M., & Sergeant, J. A. (2008). Intra-individual variability in ADHD, autism spectrum disorders and Tourette's syndrome. *Neuropsychologia*, 46(13), 3030-3041. doi: 10.1016/j.neuropsychologia.2008.06.013

Grasman, R. P., Wagenmakers, E. J., & van der Maas, H. L. (2009). On the mean and variance of response times under the diffusion model with an application to parameter estimation. *Journal of Mathematical Psychology*,*53*(2), 55-68. doi:10.1016/j.jmp.2009.01.006

Heitz, R. P. (2014). The speed-accuracy trade-off: history, physiology, methodology, and behavior. *Frontiers in neuroscience*, 8. doi:10.3389/fnins.2014.00150

Jiang, Y., Rouder, J. N., & Speckman, P. L. (2004). A note on the sampling properties of the Vincentizing (quantile averaging) procedure. *Journal of Mathematical Psychology, 48*(3), 186-195. doi:10.1016/j.jmp.2004.01.002

Karalunas, S. L., Huang-Pollock, C. L., & Nigg, J. T. (2012). Decomposing attention-deficit/hyperactivity disorder (ADHD)-related effects in response speed and variability. *Neuropsychology*, *26*(6), 684. doi: 10.1037/a0029936

Karalunas, S. L., Geurts, H. M., Konrad, K., Bender, S., & Nigg, J. T. (2014). Annual Research review: Reaction time variability in ADHD and autism spectrum disorders: Measurement and mechanisms of a proposed trans-diagnostic phenotype. *Journal of Child Psychology and Psychiatry*, *55*(6), 685-710. doi: 10.1111/jcpp.12217

MATLAB, 6.1, The MathWorks Inc., Natick, MA, (2000).

Metin, B., Roeyers, H., Wiersema, J. R., van der Meere, J. J., Thompson, M., & Sonuga-Barke, E. (2013). ADHD performance reflects inefficient but not impulsive information processing: A diffusion model analysis. *Neuropsychology*, *27*(2), 193. doi:10.1037/a0031533

Milne, E., Swettenham, J., Hansen, P., Campbell, R., Jeffries, H., & Plaisted, K. (2002). High motion coherence thresholds in children with autism. *Journal of Child Psychology and Psychiatry*, *43*(2), 255-263. doi:10.1111/1469-7610.00018

O'Riordan, M. A., Plaisted, K. C., Driver, J., & Baron-Cohen, S. (2001). Superior visual search in autism. *Journal of Experimental Psychology: Human Perception and Performance*, *27*(3), 719. doi:10.1037/0096-1523.27.3.719

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. doi:10.1016/j.tics.2012.08.009

Pellicano, E., Gibson, L., Maybery, M., Durkin, K., & Badcock, D. R. (2005). Abnormal global processing along the dorsal visual pathway in autism: a possible mechanism for weak visuospatial coherence? *Neuropsychologia*,*43*(7), 1044-1053. doi:10.1016/j.neuropsychologia.2004.10.003

Pachella, R. G. (1974). The interpretation of reaction time in information processing research, in Human Information Processing: Tutorials in Performance and Cognition, ed. B. Kantowitz (New York: Halstead Press), 41-82.

Palmer J, Huk AC, Shadlen MN (2005) The effect of stimulus strength on the speed and accuracy of a perceptual decision. *Journal of vision* 5(5):1. doi:10.1167/5.5.1

Polderman, T. J. C., Hoekstra, R. A., Posthuma, D., & Larsson, H. (2014). The co-occurrence of autistic and ADHD dimensions in adults: an etiological study in 17 770 twins. *Translational psychiatry*, *4*(9), e435. doi:10.1038/tp.2014.84

R Core Team. (2016). R: A language and environment for statistical computing. Vienna, Austria. Retrieved from http://www.R-project.org/

Ratcliff, R (1978). A theory of memory retrieval. *Psychological review*, *85*(2), 59. doi:10.1037/0033-295X.85.2.59

Ratcliff R, & McKoon G (2008). The diffusion decision model: theory and data for two-choice decision tasks. *Neural Computation*, 20(4), 873-922. doi:10.1162/neco.2008.12-06-420

Ratcliff, R., Thapar, A., & McKoon, G. (2006). Aging and individual differences in rapid two-choice decisions. *Psychonomic Bulletin & Review*,*13*(4), 626-635. doi:10.3758/BF03193973

Ratcliff R, & Tuerlinckx F (2002). Estimating parameters of the diffusion model: Approaches to dealing with contaminant reaction times and parameter variability. *Psychonomic Bulletin & Review*, *9*, 438-481. doi:10.3758/BF03196302

Rutter, M., DiLavore, P., Risi, S., Gotham, K., & Bishop, S. L. (2002).*Autism diagnostic observation schedule: ADOS: Manual*. Los Angeles, CA: Western Psychological Services.

Seli, P., Jonker, T. R., Cheyne, J. A., & Smilek, D. (2013). Enhancing SART Validity by Statistically Controlling Speed-Accuracy Trade-Offs. *Frontiers in Psychology*, 4, 265. doi:10.3389/fpsyg.2013.00265

Simmons, D. R., Robertson, A. E., McKay, L. S., Toal, E., McAleer, P., & Pollick, F. E. (2009). Vision in autism spectrum disorders. *Vision research*,*49*(22), 2705-2739. doi:10.1016/j.visres.2009.08.005

Townsend, J. T., & Ashby, F. G. (1983). Stochastic modeling of elementary psychological processes. CUP Archive.

Stone JV (2014) Using reaction times and binary responses to estimate psychophysical performance: an information theoretic analysis. *Frontiers in Neuroscience* 8:35. doi:10.3389/fnins.2014.00035

Vandekerckhove, J., & Tuerlinckx, F. (2008). Diffusion model analysis with MATLAB: A DMAT primer. *Behavior Research Methods*, *40*(1), 61-72.doi:10.3758/BRM.40.1.61

Wagenmakers, E. J., Van Der Maas, H. L., & Grasman, R. P. (2007). An EZ-diffusion model for response time and accuracy. *Psychonomic Bulletin & Review*, 14(1), 3-22. doi:10.3758/BF03194023

Wechsler, D. (1999). *Wechsler Abbreviated Scale of Intelligence*. San Antonio, TX: The Psychological Corporation.

White, C. N., Ratcliff, R., Vasey, M. W., & McKoon, G. (2010). Using diffusion models to understand clinical disorders. *Journal of Mathematical Psychology, 54*(1), 39-52. doi:10.1016/j.jmp.2010.01.004

Wickelgren, W. A. (1977). Speed-accuracy trade-off and information processing dynamics. *Acta Psychologica*, 41(1), 67-85. doi:10.1016/0001-6918(77)90012-9

Footnote

[1] The Autism Spectrum Quotient (AQ, Baron-Cohen et al.) was not used as part of the protocol for this study and therefore is not reported for all participants. However, we had access to the AQ score of the participant who did not reach cut-off for ASD on the ADOS and did not complete the SRS-2 so were able to take this into account when considering whether or not it was appropriate to retain this participant in the analyses.

Table 1

Participant Characteristics

Variable	ASD Group		NT Group		*p*
	Mean	SD	Mean	SD	
Age in years	33.85	14.24	34.40	14.66	.89
MR T-score	59.32	7.02	56.26	7.92	.14
SRS T-score	72.52	10.46	50.39	8.39	<.001
ADOS score	10.17	4.2			

Note. The Matrix Reasoning (MR) task is from Wechsler Abbreviated Scales of Intelligence (Wechsler, 1999). The Social Responsiveness Scale (SRS-2) is from Constantino & Gruber (2012). The Autism Diagnostic Observational Schedule (ADOS) score is calculated from the communication and social interaction subscales.

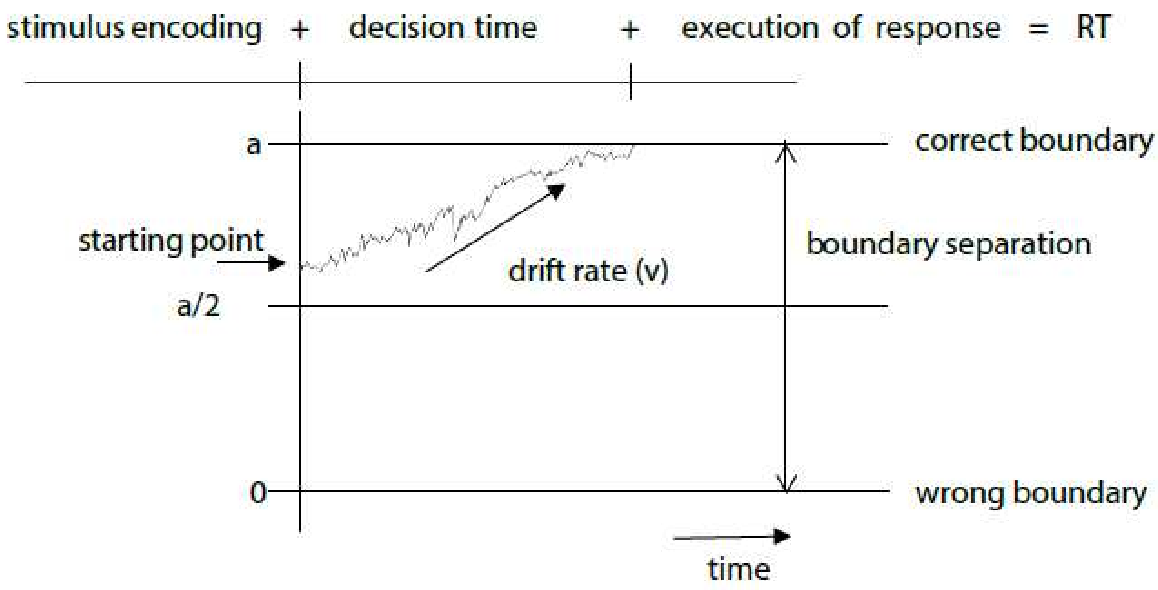

Figure 1. Graphical representation of the full DDM (Ratcliff & McKoon,2008).

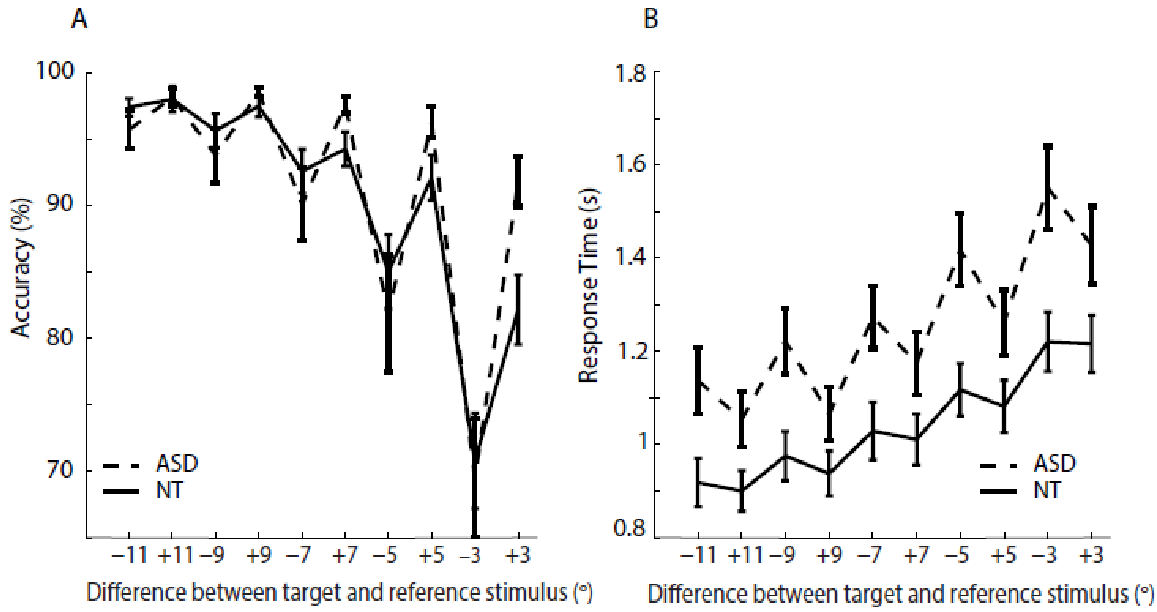

Figure 2. Accuracy and response time data. **A** shows percentage of trials correct and **B** shows mean response time (for correct responses only) for the two groups of participants (ASD shown by dashed lines) across the different conditions. Anticlockwise rotations are indicated with - ; clockwise rotations are indicated with +. Error bars represent standard error of the mean.

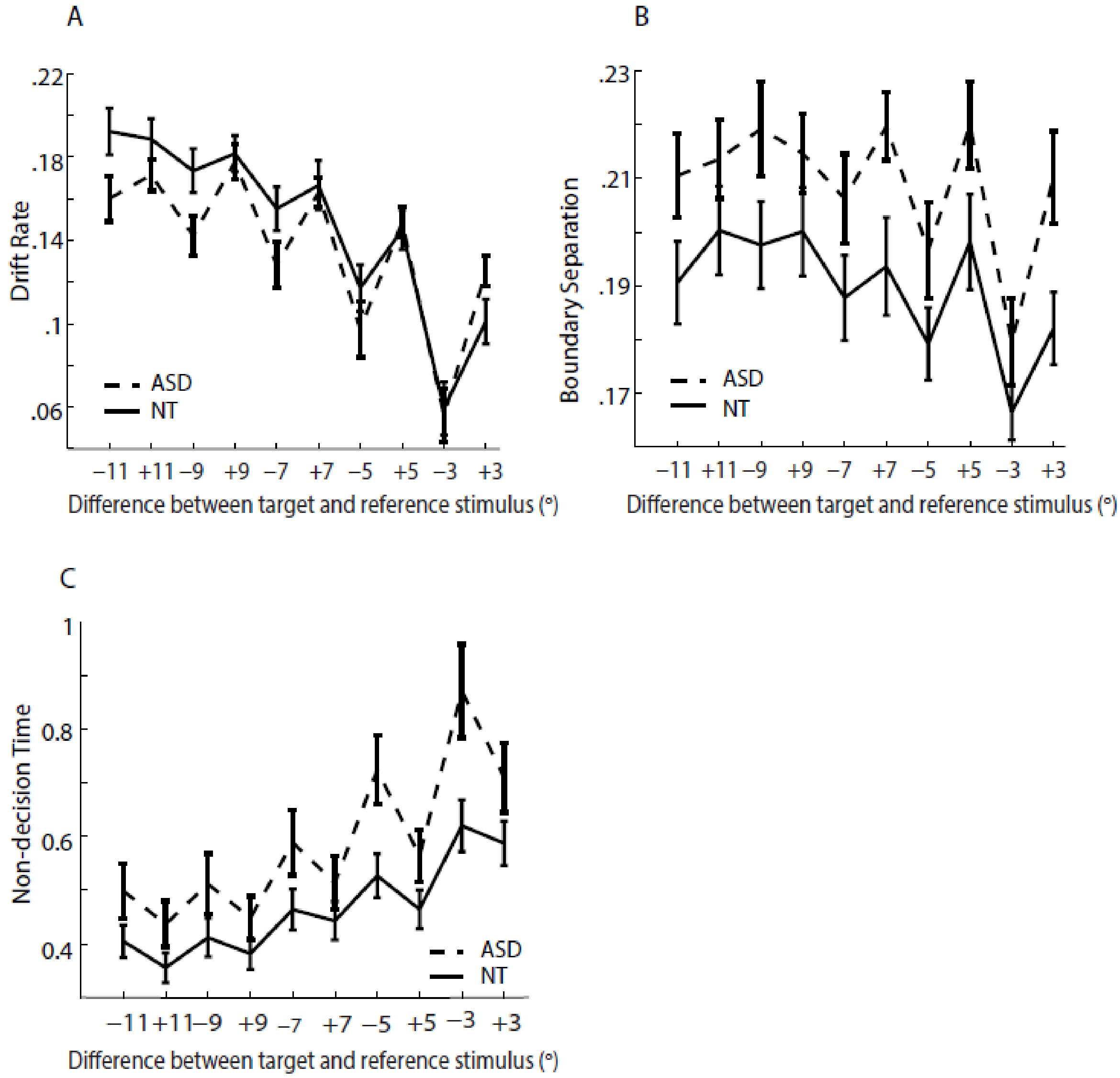

Figure 3. Modelled parameters. **A** shows mean drift rate, **B** shows mean boundary separation and **C** shows mean non-decision time for the two groups of participants (ASD shown by dashed lines) across the different conditions. Anticlockwise rotations are indicated with - ; clockwise rotations are indicated with +. Error bars represent standard error of the mean.

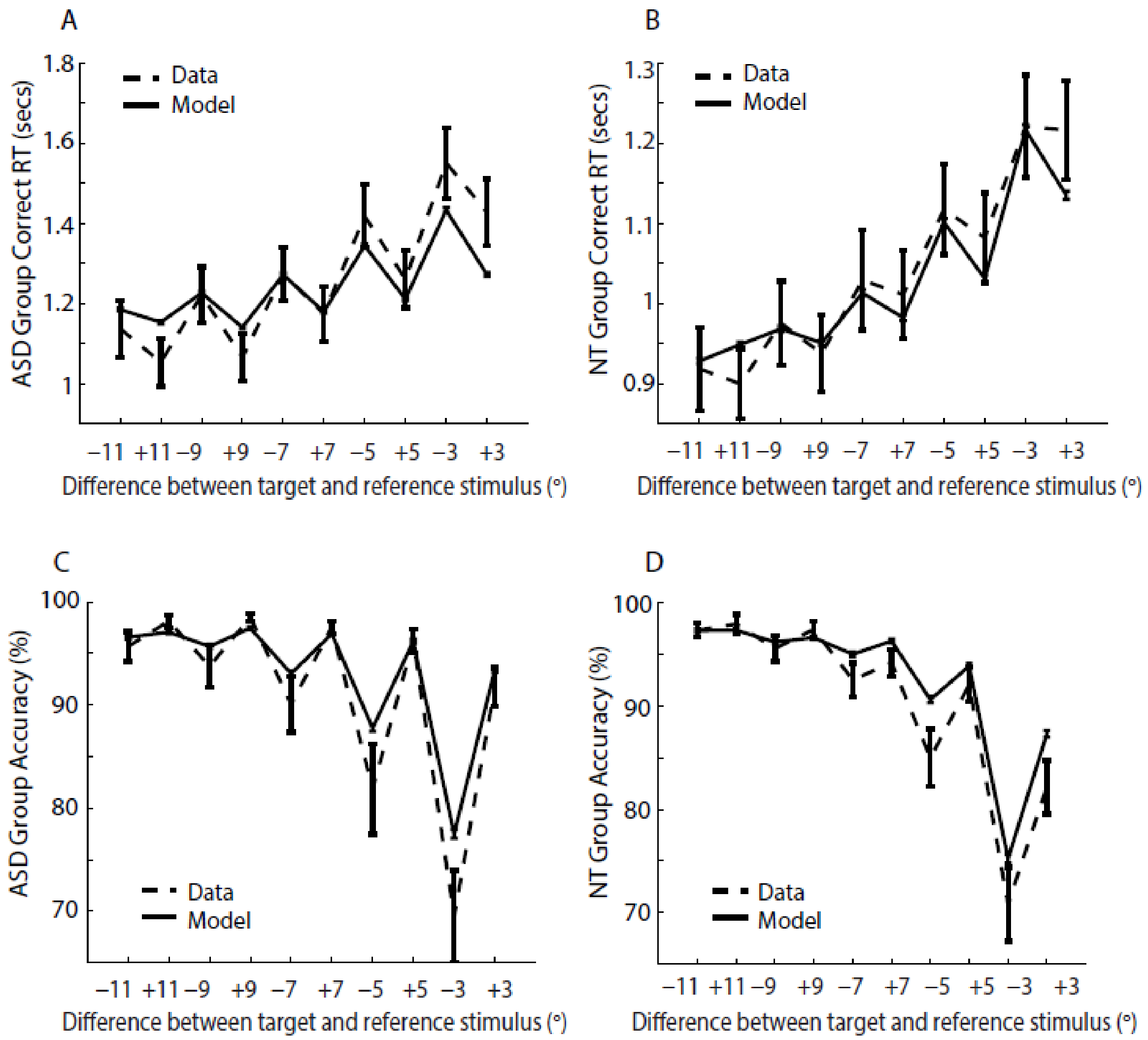

Figure 4. Simulated data. **A** shows comparisons between mean response time (for correct responses only) for the ASD group and for the simulated data **B** shows comparisons between mean response time (for correct responses only) for the TD group and for the simulated data **C** shows comparisons between percentage of trials correct for the ASD group and for the simulated data **D** shows comparisons between percentage of trials correct for the TD group and for the simulated data. Anticlockwise rotations are indicated with - ; clockwise rotations are indicated with +. Error bars represent standard error of the mean.