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Article:

Pirrone, A., Johnson, I., Stafford, T. et al. (2018) A diffusion model decomposition of orientation discrimination in children with Autism Spectrum Disorder. *European Journal of Developmental Psychology*, 17 (2). pp. 213-230. ISSN: 1740-5629

<https://doi.org/10.1080/17405629.2018.1561364>

This is an Accepted Manuscript of an article published by Taylor & Francis in *European Journal of Developmental Psychology* on 27/12/2018, available online:
<http://www.tandfonline.com/17405629.2018.1561364>

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A diffusion model decomposition of orientation discrimination in children with Autism Spectrum Disorder (ASD)

Abstract

Children with and without ASD performed an orientation discrimination task, in which the difficulty of the discrimination was equated across individuals. Behavioural results showed that subjects with ASD were slower in making a decision. A computational decomposition of data was performed and modelled parameters indicated that: (i) participants with ASD adopted a more conservative response criterion and (ii) motor response did not differ between groups. Our results confirm that differences in reaction times (RTs) and/or accuracy between participants with and without ASD in orientation discrimination may be related to differences in response conservativeness rather than in stimulus discriminability, in line with data previously reported from adults (Pirrone, Dickinson, Gomez, Stafford & Milne, 2017). This result has important implications for studies that have claimed impairments/enhancements in ASD on the basis of differences in RTs and/or accuracy alone.

Keywords: autism spectrum disorder, drift diffusion model, speed-accuracy trade-off, orientation discrimination

Autism Spectrum Disorder (ASD) is characterised by differences in communication, social interaction and sensorimotor abilities. Research investigating perception in ASD has provided opposing results regarding perceptual abilities which, depending on the specific field or experimental paradigm adopted, have supported claims of impairments or enhancements (e.g. Deruelle, Rondan, Gepner & Tardif, 2004; Mottron, Peretz, & Menard, 2000; Milne, Swettenham, Hansen, Campbell, Jeffries & Plaisted., 2002; Bertone, Mottron, Jelenic & Faubert, 2003). Many existing studies investigating perception in individuals with ASD have used the two-alternative forced choice method (2AFC) whereby participants are asked to select a single response out of a choice of two to indicate a judgement about a specific stimulus. Example responses include: “the target is present / absent”, “the dots are moving to the left / right” and “the grating is slanted clockwise / anticlockwise”. In paradigms such as these, the dependent variables of accuracy and / or response time are used to inform conclusions about perceptual function. Typically, these paradigms involve one-shot, ‘simple’ decisions that are made within seconds. However, even ‘simple’ decisions are determined by a number of underlying processes: the participant has to encode the stimulus, make a decision weighing

the stimulus information and the costs and benefits of different response options, and execute the motor response by pressing a button on the keyboard in order to indicate the response. This central component - the decision time - will be influenced by the sensitivity of their perception, the difficulty of the task, the response conservativeness of participants and pre-existing bias towards or away from available response options. Importantly, each of these factors can have systematic effects on response times and on accuracy. As difficulty increases, RTs increase and accuracy decreases; as response conservativeness increases, RTs and accuracy increase; as the bias towards a response increases, fast RTs towards the biased alternative are predicted and slow RTs towards the opposite alternative are predicted; and as the time to encode the stimulus or execute the motor response increases, RTs increase but accuracy is unaffected.

It is clear that a difference in RTs and/or accuracy between two groups can be determined by any combination of the processes described above, and that single-measure data analysis (i.e., response time or accuracy alone) cannot disambiguate the contribution of these factors to decisions on a particular task. Unfortunately, there are myriad examples of studies that purport to provide evidence for domain-specific information processing differences between individuals with and without ASD on the basis of differences in RTs or accuracy alone. As has been argued previously (see Pirrone et al., 2017), it is possible that some of these differences may reflect alteration in aspects of decision making in ASD rather than a domain-specific neuropathological difference. Fortunately, it is possible to use computational models of decision making to isolate the contribution of the different factors affecting a decision. In particular, the Drift Diffusion Model (DDM; Ratcliff & McKoon, 2008) has been shown to provide a powerful description of decision making in various domains (for a review see Ratcliff & McKoon, 2008). In the DDM, the decision maker integrates difference in evidence supporting two alternatives until a decision criterion for one of the two alternatives is reached and a decision is selected. Four principal parameters are computed from the DDM: drift rate, which is the parameter that relates to stimulus discriminability; boundary separation, which is the parameter that captures the speed-accuracy trade-off; the starting point, which is the parameter that captures the bias towards a

response; and the non-decision time which is the parameter that captures the time to encode the stimulus and execute the motor response.

Here we further investigate the mechanisms underlying 2AFC decision making in individuals, specifically children, with ASD, using the DDM. By fitting the DDM to participant's data we can recover estimates for the parameter values which we hypothesise underlie their decision making. In particular, the DDM allows us to extract estimates for differences in speed-accuracy trade-off between groups, unlike direct measures of speed or accuracy alone. The benefits of performing a computational decomposition of data using the DDM when comparing groups have been widely shown (see, Ratcliff & McKoon, 2008). For example, in one study where RTs were found to be slower in older participants compared to younger participants, DDM parameters revealed that this arose from differences in boundary separation and non-decision time rather than differences in information processing as had previously been assumed (Ratcliff, Thapar & McKoon, 2006). This finding is important as it demonstrates that results that were previously interpreted as providing evidence for a difference in stimulus discriminability in older adults, are instead due to differences in response criterion and motor ability, thus demonstrating the increased understanding of perceptual decision making that can be afforded by using the DDM.

The DDM has also been used to investigate orientation discrimination in adults with and without ASD (Pirrone et al., 2017). Previous research on orientation discrimination in ASD has mostly focused on the measurement of orientation sensitivity via the use of psychophysical staircase methods, and conflicting results have been reported including impairments for ASD participants (Sysoeva et al., 2015), no difference between the two groups (Shafai, Armstrong, Iarocci & Oruc, 2015) and enhancements for ASD participants (Bertone, Mottron, Jelenic & Faubert, 2005; Dickinson, Jones & Milne, 2014 - for participants with high autistic traits; Dickinson, Bruyns-Haylett, Smith, Jones and Milne, 2016). In a recent investigation of perceptual decision making in ASD (Pirrone et al. 2017), adults with and without ASD performed an orientation discrimination task in which they were asked to decide whether a target stimulus was oriented clockwise or anticlockwise with respect to a

reference stimulus. Results showed no significant difference in orientation sensitivity between the groups, although there was a trend towards enhanced discrimination in the adults with ASD, especially when the difference between the target and the reference stimulus was small. However, it was also found that participants with ASD were slower to respond to the stimuli, and the DDM decomposition of the data showed that slower RTs in participants with ASD compared to neurotypical participants were due to differences in response criterion and non-decision time. Importantly, the two groups did not differ in drift rate, suggesting that there was no difference in stimulus discriminability between the two groups. However, a number of limitations existed in Pirrone et al. (2017). For example, the target stimulus always appeared on the right of the screen and the reference was always tilted 45° clockwise (hence ‘pointing’ towards the right); as such the design of the paradigm may have resulted in participants being facilitated in answering clockwise given the interaction of the target stimulus location and of the standard stimulus orientation. A further limitation of the results presented in Pirrone et al (2017) is that the number of trials per condition was low ($N = 20$) and the accuracy of participants was close to ceiling level. Because of the low number of trials per condition, authors were limited in the complexity of the decision making model they could fit. They therefore used a simplified version of the DDM, the EZ-DDM (Wagenmakers, Van Der Maas & Grasman 2007), which estimates drift rates, boundary separation and non-decision time, for each participant and condition separately, and makes the assumption that there is no response bias and no across-trial variability in parameters.

Here, we revisit the question of whether the processes underlying perceptual decision making are altered in individuals with ASD. We developed a new experimental paradigm in which the limitations of Pirrone et al. (2017) were directly addressed. In particular, (i) participants decided whether a target stimulus was oriented clockwise or anticlockwise with respect to a vertical line which appeared above the stimulus and (ii) participants performed 70 trials per condition. In addition, by using a psychophysical estimation procedure for each subject, we estimated the difficulty for which 65 or 85 % accuracy was predicted; in this way accuracy is not at ceiling level and DDM parameters can be

measured independently from any potential group differences in task-difficulty, and we can mainly focus on our parameter of interest – the boundary separation.

Method

Participants

Two groups of participants were recruited for the study: children with a diagnosis of an autism spectrum disorder (ASD), and children who were free from any neurodevelopmental disorders (hereafter referred to as the neurotypical - NT - group). Inclusion criteria were: being aged between 6 and 16 and having normal or corrected-to-normal binocular vision. Exclusion criteria for all participants included a history of epilepsy, seizures or migraines. Further exclusion criteria for the NT group included having a first-degree relative with an ASD diagnosis and / or having ever been referred for an ASD diagnosis. A total of 29 participants were recruited. Twelve participants (four females) had received an ASD diagnosis from an experienced clinical psychologist or from a multi-disciplinary team. Of these participants, six were diagnosed with ASD and six were diagnosed with Asperger's syndrome. Four participants, all of whom had a primary diagnosis of ASD, were comorbid for ADHD. Of the NT participants, 10 were females. Participants were recruited through our research group participant database, special education charities, social media advertisements and the staff and student University volunteer mailing list. Demographic details for the two groups of participants are presented in Table 1. The study received ethical approval from the Departmental ethics subcommittee and all procedures were carried out in accordance with the Declaration of Helsinki.

A number of baseline variables, described below and reported in Table 1, were measured in order to better characterise the two samples. Non-verbal reasoning ability was measured with the Matrix Reasoning task of the Weschler Abbreviated Scales of Intelligence (WASI; Wechsler, 1999) and was used here as a proxy for non-verbal IQ. Given time constraints / participant burden associated with data collection (which in our case included multiple experiments and questionnaires/tests), we decided to include only the matrix reasoning sub-task from the WASI and did not also administer the Block

Design task.

Independent samples t-test indicated that the participants with ASD obtained lower Matrix Reasoning scores than the NT participants. Binocular vision was measured using Keeler LogMAR crowded cards (Keeler Limited, UK). The cut-off for having sufficient acuity for this task was having a LogMAR score of 0.2 or below (Snellen equivalent of 6/9.5). All participants met this cut-off and there was no difference in visual acuity between the participants with and without ASD. Parents / guardians of all participants completed the Social Responsiveness Scale- Revised (SRS-2), which is a 65-item questionnaire that measures reciprocal social interaction. A t-score of 59 or below on the SRS is considered to be within normal limits, whereas a T-score of 60 or above is considered to reflect clinically significant difficulties in reciprocal social behaviour. As expected, participants with ASD obtained significantly higher SRS t-scores than participants without ASD. All of the NT participants obtained SRS T-scores below 59 and all of the participants in the ASD group obtained SRS T-scores above 60. As expected, participants with ASD obtained significantly higher SRS t-scores than participants without ASD. Finally, the participants with ASD, but not the NT group, completed either module 3 or 4 from the ADOS-II. Eight of the participants scored above the ADOS cut-off for autism, two scored above the ADOS cut-off for autism spectrum. One participant did not complete the ADOS as he became distressed following experimenter attempts to engage him in imaginative play. Although we do not have a full ADOS score for this participant, it is reasonable to assume that this participant would have scored above the cut-off autism. The other participant completed the ADOS but obtained a combined communication and social interaction score of 4, i.e. in the non-spectrum range. Given that this participant obtained an SRS score above 60 and had a clinical diagnosis of ASD, their data were retained in the analyses.

Insert Table 1 about here please

Perceptual Task

The experimental task consisted of two parts: an initial 2AFC task (calibration) that measured

orientation discrimination thresholds to off-vertical gratings using a method of constant stimuli design, and a second 2AFC task that required participants to indicate whether a grating was tilted clockwise or anticlockwise with respect to a reference vertical line presented on top of the grating. Stimuli oriented at each participant's 65% and 85% accuracy thresholds obtained during the calibration task were presented in the second task. As such this second task involved making judgements that were harder (65% accuracy threshold) and easier (85% accuracy threshold) using stimuli tilted at angles that were specific to each participant's psychometric function. The task and stimuli were created using PsychoPy (Pierce, 2007). Stimuli consisted of a single sine wave grating with a spatial frequency of 1 cycle per degree (cpd). The border of the grating faded out into a grey background and there was a red fixation dot in the middle of the grating. Stimuli were presented on a linearised Lenovo laptop screen with a spatial resolution of 1366 x 768 pixels and a temporal resolution of 60 Hz.

Testing took place either in the University Psychology department, or in the participant's home. The matrix reasoning test was usually administered first as the participants with ASD were generally more comfortable with tasks that required less verbal interaction. Four participants from the ASD group completed the tasks over the course of two days, the other participants completed all of the tasks in one day.

Orientation Discrimination Task 1: Calibration

Participants viewed the laptop screen at a 57 cm distance and were asked to decide, by button press on the keyboard, whether a target reference was oriented clockwise or anticlockwise with respect to a black vertical line that appeared on top of the grating. Subjects were required to use their right hand and to press left on the keyboard using their second finger for an anticlockwise response, and to press right using their third finger for a clockwise response. This task consisted of 5 levels of difference in angle between the target and the reference (0.1°, 0.5°, 1.0°, 2.0°, 5.0°) x 2 levels of rotation (clockwise and anticlockwise) x 28 repetitions, equalling a total of 280 trials. Trials were presented in

random order and no accuracy feedback was provided to participants. After each consecutive 40 trials participants could take a self-paced break. For each participant, we computed the difference in angle between the reference and the target for which 65% and 85% accuracy was predicted. We did so by interpolating the psychometric curve estimated with the model free procedure described in Zchaluk and Foster (2009), using MATLAB scripts made available by the authors.

Orientation Discrimination Task 2: Experiment

For the second experimental task we used, for each participant, the difference in angle between reference and target for which 65% and 85% accuracy was predicted using the above described method. For example if for a participant a difference of 2° predicted 65% accuracy, and a difference of 4° predicted an accuracy of 85%, the participant would only be presented with 2° and 4° discriminations, clockwise and anticlockwise. The apparatus was the same as for the calibration. This task consisted of 2 levels of difficulty (65% and 85% expected accuracy) x 2 levels of rotation (clockwise and anticlockwise) x 70 repetitions, equalling a total of 280 trials. Trials were presented in random order and no accuracy feedback was provided to participants. Also here, after each consecutive 40 trials participants could take a self-paced break.

Results

We analysed our data using the free and open-source software JASP (JASP Team, 2018). In particular, we performed Bayesian ANOVAs, in which the posterior probability for all combination of models that could have generated the data are computed. For example if an ANOVA includes only one factor, the Bayesian ANOVA calculates posterior probabilities for the null model and for the model

including the factor of interest. The Bayes Factor (BF) then quantifies the support of a specific model over the null model, and it allows to select the model that is most likely to have generated the data. With regards to the above example, the BF enables the researcher to answer how likely it is that the model that includes the factor of interest generated the data compared to the null model. We adopted the classification scheme reported by JASP, that is adjusted from Jeffreys (1961), as reported in Table 2. For a more in depth discussion of Bayesian principles and JASP, see Marsman and Wagenmakers (2017).

Insert Table 2 about here please

Orientation Discrimination Thresholds (obtained from calibration task)

The mean 65% and 85% correct thresholds were $.52^\circ$ ($.54^\circ$) and 1.55° (1.16°) for the ASD group, and $.57^\circ$ ($.38^\circ$) and 1.72° (1.20°) for the NT group. A Bayesian repeated measures ANOVA with difficulty and orientation as factors, group (ASD vs. NT) as between subject factor and matrix reasoning scores as covariate, showed that the best model that explained the data was the one that included only the main effect of difficulty (i.e., and not a main or interaction effect with group), $BF = 796356$; meaning that, as predicted, thresholds were lower for conditions for which the expected accuracy was 65% compared to conditions for which the expected accuracy was 85%.

Observed Variables (obtained from experimental task)

RTs below .3 seconds and above 3 seconds were removed and this resulted in 8.42% of the data being removed. These cut-offs are based on previous literature according to which RTs below .3 seconds and above 3 seconds are less likely to be generated from a diffusion process (Ratcliff, Thapar and

McKoon, 2006), but can be either considered fast guesses or attentional lapses. It is important to remove these data since parameters estimates of the DDM can be strongly affected, especially by fast RTs (Ratcliff & Tuerlinckx, 2002).

In Figure 1 we show the effects of difficulty and rotation on accuracy, separately for the two groups. A Bayesian repeated measures ANOVA with difficulty and orientation as factors, group as between subject factor and matrix reasoning scores as covariate, showed that the best model was the one that included only the main effect of difficulty and orientation, and their interaction, $BF = 1.838 \times 10^{10}$. As shown in Figure 1, as difficulty increased, decisions were less accurate; furthermore, subjects were more accurate for clockwise compared to anticlockwise judgements. However, Figure 1 shows that subjects were more accurate for clockwise judgements only when the expected accuracy was 65 %.

Insert Figure 1 about here please

In Figure 2 we show the effects of difficulty and rotation on correct RTs separately for the two groups. Regarding RTs, a Bayesian repeated measures ANOVA showed that the best model was the one that included the main effects of difficulty and group, $BF = 8021$. Figure 2 shows that, in line with our hypothesis, ASD subjects were generally slower compared to NT subjects. Table 3 reports mean RTs for subjects in the ASD and NT group; the difference can be seen to be of about 200 ms, a considerable difference for the type of task and considering that mean RTs were always below 1.5 seconds. Furthermore, as expected by our manipulation, subjects were faster in easier compared to difficult conditions.

Insert Figure 2 about here please

Model Fitting

In order to estimate the parameters of the DDM, we used the Diffusion Model Analysis Toolbox for MATLAB (DMAT; Vandekerckhove & Tuerlinckx, 2007; 2008). Using DMAT we estimated parameters using a chi-square estimation procedure of the data represented in bins. In order to avoid overfitting, we selected a model in which the boundary separation, the non-decision time and the starting point were constant across conditions. This is common practice in decision modelling (Vandekerckhove & Tuerlinckx, 2007; 2008) and the rationale behind this choice is that such parameters are not stimulus contingent and they are set before the stimulus appears. The drift rate was instead free to vary across conditions. However, given our calibration task in which we equated difficulty across participants, we did not expect a group difference in drift rate. Across-trial variabilities require a great amount of trials (usually hundreds) in order to be estimated and they only minimally increase the fit; furthermore, error messages provided by DMAT indicated that we could not correctly estimate such parameters. For these reasons, we set across trials variabilities (in non-decision time, drift and starting point) to an arbitrary level that approached zero, .001.

Parameters estimated from the model fitting are reported in Table 4.

Insert Table 3 about here please

Regarding drift rate, a Bayesian repeated measures ANOVA with difficulty and orientation as factors, group as between subject factor and matrix reasoning scores as a covariate, showed that the best model that explained the data was the one that included only the main effects of difficulty, $BF = 3.415 \times 10^{12}$. As expected, drift rates were higher for easier discriminations but did not differ between the two groups.

Regarding the boundary separation, a Bayesian ANCOVA with group as fixed factor and matrix

reasoning scores as covariate, showed that the model including the main effect of group model was preferred among all models, $BF = 4.713$, suggesting that ASD subjects had a more conservative decision criterion compared to NT subjects.

For both the non-decision time and the starting point, the BF did not show support for group differences; the BF for the model including group differences was respectively, .376 for the non-decision time and .821 for the starting point.

In order to show in absolute terms how good the estimated parameters are, we simulated a DDM for each subject with the same number of trials as in the experiment. Subsequently, we computed mean accuracy and mean RTs for the simulated data, in the same way in which mean accuracy and mean RTs were computed for the observed data. Figure 1 shows comparisons of mean accuracy for the model and the data. Figure 2 shows comparisons of RTs for the model and the data. In both cases the model shows good agreement with the data, confirming that the parameters of the DDM that we recovered can account well for the data.

Insert Table 4 about here please

Discussion

Here, using the DDM, we have performed a computational decomposition of orientation discrimination judgements in children with ASD. We found that, when parameters of the experimental design were manipulated so that accuracy was equated across groups, children with ASD responded more slowly than NT children, showing on average a 200 ms increase in response time. The fact that the DDM analyses showed that children with ASD have significantly wider boundary separation than NT participants suggests that slower responses in ASD are due to a more conservative speed-accuracy trade-off, i.e. a more 'slow and careful' approach. Importantly, the parameter that captured stimulus discriminability, the drift rate, did not differ significantly between the two groups and was carefully controlled to be equated across individuals with a calibration task, indicating that any differences in response time between the two groups are unlikely to be due to differences in perceptual sensitivity. This result is in line with previous work which showed that increased RTs in adults with ASD compared to NT participants may be attributed to an increase in response conservativeness rather than to a difference in stimulus discriminability/sensitivity (Pirrone et al., 2017). This finding has important implications for a number of studies that have drawn conclusions regarding perceptual and / or cognitive deficits or enhancements in ASD on the basis of 2AFC tasks. In particular, there is the risk that differences in response criterion have been misinterpreted as differences in stimulus discriminability. This study highlights that estimates of differences in stimulus discriminability in ASD that are based only on accuracy or RTs could be overestimated or underestimated, given possible speed-accuracy trade-off confounds as is demonstrated here.

Previous work has shown that orientation discrimination thresholds are lower (indicating increased sensitivity) in adults with autism (Dickinson et al. 2016). Here, in the initial calibration task there was no significant difference in orientation discrimination threshold between the participants with and without ASD, although there was a trend towards lower thresholds in participants with ASD. It is possible that a larger sample size would have generated a significant difference between the discrimination thresholds of the participants with and without ASD. However, the result of increased

boundary separation in the ASD group combined with no group difference in drift rate, further suggests that lower threshold could be explained by increased response conservativeness in ASD – participants with ASD spend more time on each trial and as a consequence make more accurate responses and have lower discrimination thresholds.

We believe that our results have important consequences for studies which, on the basis of differences in accuracy and RTs alone, have reported evidence for a difference in stimulus discriminability without taking into account speed-accuracy trade-off confounds. Future research should investigate whether this result can be extended to other domains, and should investigate the mechanisms that underlie increased response caution in ASD. It is important to note that, the result of increased boundary separation from a DDM perspective is a descriptive account that does not tell us anything about the mechanisms and causes that generate it (for a discussion about the mechanisms that may underlie increased response conservativeness in ASD, see Pirrone, Wen, Li, Baker & Milne, 2018).

Although our results do not allow to reconcile the varied results of impaired, equal, or enhanced performance in orientation discrimination between subjects with and without ASD, they highlight – together with Pirrone et al. (2017) - that any claim regarding orientation discrimination in ASD should be made only *after* having removed confounds of response conservativeness, by focusing on parametric measures of sensitivity to stimulus alone, such as drift rate. Otherwise, the risk is that data focusing on reaction times only may conclude for an impairment given increased reaction times in ASD, while conversely work focusing on accuracy measures, may conclude for an enhancement in ASD given higher accuracy in orientation discrimination. That is, differences in response conservativeness may be misinterpreted as differences in orientation discrimination, which we believe could in part be a factor explaining previous contrastive results and which could be an important factor to consider for future reviews of orientation discrimination in ASD.

There are three main limitations to the data which are: (i) small sample size, (ii) the fact that the matrix reasoning scores are significantly lower for participants with ASD than for NT participants and (iii) the fact that some of the participants with ASD also had co-morbid ADHD. With regards to the

first point, although the sample size is low, our data allowed us to appreciate a difference between the two groups for the DDM parameter of interest – the boundary separation, and for RTs, a particularly strong difference of about 200 ms. However, it is possible that some of the null effects that we found here may become significant were a larger sample to be recruited. Nevertheless, this does not detract from the main finding of our work – that of a clear difference in boundary separation between children with and without ASD. Regarding the second point, matrix reasoning scores were always entered as a covariate, and they never affected behavioural or modelling results, thus indicating that the difference in non-verbal reasoning identified between the two groups did not significantly impact on the results reported. Regarding the third point, recent research has shown that participants with ADHD have a decrease in stimulus sensitivity while they do not differ in boundary separation compared to NT participants (Karalunas, Huang-Pollock, & Nigg, 2012; Metin et al., 2013), meaning that ADHD co-morbidity in our sample should result in worse discrimination in ASD participants and a decrease in drift rate. However, we did not observe lower drift rate in the participants with ASD, or in the threshold to achieve 65 or 85% accuracy. Furthermore, results are unchanged if the four participants with ADHD are removed from the analysis. Nevertheless, it would be useful to measure the parameters described above in a further sample of children who have ASD and not ADHD, and to compare this with a matched sample of children who have both ASD and ADHD in order to fully understand the effect that co-morbid ADHD may have on perceptual decision making in ASD.

In sum, our results confirm the power of the DDM decomposition in generating valid conclusions from data and support the hypothesis that previous studies that have shown a difference in stimulus discriminability in participants with ASD might need to be reconsidered and controlled for speed-accuracy trade-off effects.

Author note

Funding details: this work was supported, in part, by a small grant from the Experimental Psychology Society. The funding source had no other role other than financial support. All authors declare that they have no conflict of interest.

Ethical approval: all procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration.

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

Acknowledgements: the authors sincerely thank all of the participants and their families for taking part in the study, and Al Ingall for her contribution to data collection.

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	ASD (N = 12)	NT (N = 17)	Group Comparison
Mean age in years (<i>SD</i>)	11.92 (3.19)	11.46 (2.44)	$t(27) < 1, p = .67$
Range	6.96 – 16.16	8.39 – 15.71	
Mean MR T-score (<i>SD</i>)	53.67 (5.33)	59.41 (5.77)	$t(27) = 2.7, p = .011$
Range	46 - 66	49 – 72	
Mean LogMAR score (<i>SD</i>)	-.019 (0.16)	-.081 (0.13)	$t(27) = 1.14, p = .26$
Range	-.275 - .200	-.275 - .175	
Mean SRS T-score (<i>SD</i>)	83.67 (8.76)	44.71 (5.45)	$t(27) = 14.78, p < .001$
Range	62 - 90	39 - 58	
Mean ADOS-II score (<i>SD</i>)	13.63 (7.05)		
Range	4 - 20		

Table 1: Participant Characteristics.

Bayes Factor	Evidence category
> 100	Extreme evidence for H1
30 - 100	Very strong evidence for H1
10 - 30	Strong evidence for H1
3 - 10	Moderate evidence for H1
1 - 3	Anecdotal evidence for H1
1	No evidence
1/3 - 1	Anecdotal evidence for H0
1/10 – 1/3	Moderate evidence for H0
1/30 – 1/10	Strong evidence for H0
1/100 – 1/30	Very strong evidence for H0
< 1/100	Extreme evidence for H0

Table 2: Classification scheme of Bayes Factor, taken from Lee & Wagenmakers (2014), adjusted from Jeffreys (1961).

Expected difficulty	Orientation	Group	M (s)	SD (s)
85%	Clockwise	ASD	1.14	0.308
		NT	0.929	0.244
	Anticlockwise	ASD	1.185	0.402
		NT	0.923	0.230
65%	Clockwise	ASD	1.23	0.380
		NT	0.984	0.269
	Anticlockwise	ASD	1.261	0.344
		NT	1.063	0.235

Table 3: Mean reaction times, in seconds, for the ASD and the NT group.

Parameter	Group	Mean	SD
Boundary	ASD	0.21	0.044
	NT	0.177	0.026
Non-decision time	ASD	0.386	0.247
	NT	0.359	0.079
Starting point	ASD	0.52	0.03
	NT	0.499	0.04
Drift -85 %	ASD	0.103	0.04
	NT	0.121	0.053
Drift -65 %	ASD	0.018	0.036
	NT	0.034	0.042
Drift +65 %	ASD	0.07	0.041
	NT	0.045	0.038
Drift +85 %	ASD	0.107	0.047
	NT	0.122	0.059

Table 4. Parameters of the DDM.

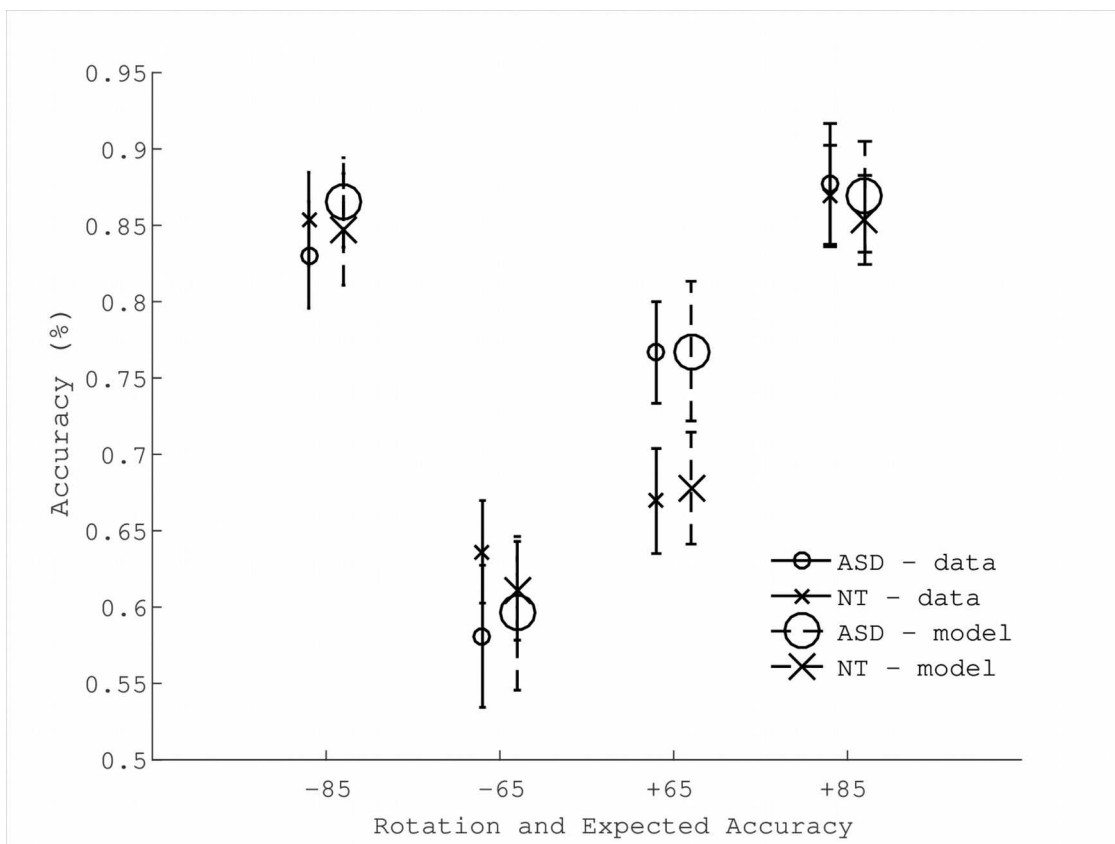


Figure 1: Observed mean accuracy from the data for the two groups of participants across the different conditions, and simulated mean accuracy from the model for the two groups of participants across the different conditions. Anticlockwise rotations are indicated with - ; clockwise rotations are indicated with +. Error bars represent standard error of the mean

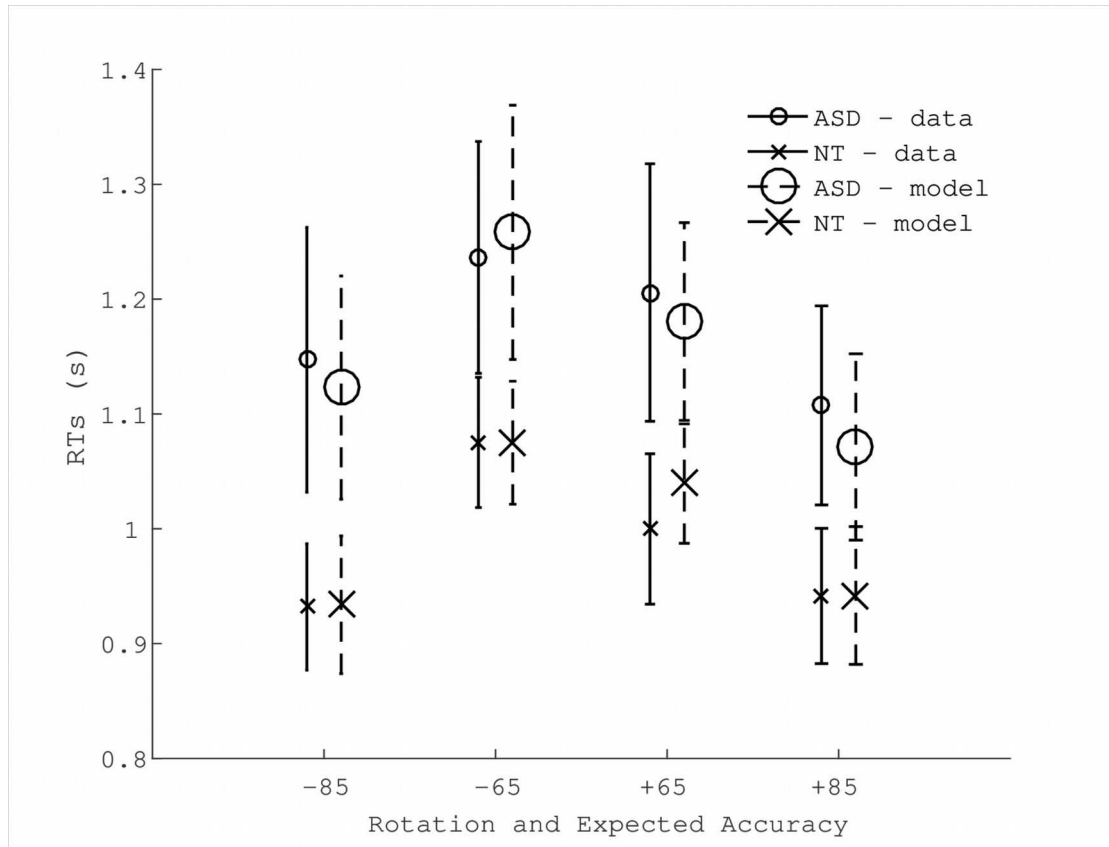


Figure 2: Observed mean correct RTs from the data for the two groups of participants across the different conditions, and simulated mean correct RTs accuracy from the model for the two groups of participants across the different conditions. Anticlockwise rotations are indicated with - ; clockwise rotations are indicated with +. Error bars represent standard error of the mean.