**Autistic traits are related to worse performance in a volatile reward learning task despite
adaptive learning rates**

Judith Goris¹, Massimo Silvetti^{2,1}, Tom Verguts¹, Jan R. Wiersema³, Marcel Brass¹, & Senne
Braem^{4,1}

¹ Department of Experimental Psychology, Ghent University, Henri Dunantlaan 2, 9000 Ghent,
Belgium

² Computational and Translational Neuroscience Laboratory (CTNLab), Institute of Cognitive
Sciences and Technologies, National Research Council, Via San Martino della Battaglia 44,
00185 Rome, Italy

³ Department of Experimental Clinical and Health Psychology, Ghent University, Henri
Dunantlaan 2, 9000 Ghent, Belgium

⁴ Department of Psychology, Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussel

Correspondence:

Judith Goris

Department of Experimental Psychology

Henri Dunantlaan 2

B – 9000 Ghent

BELGIUM

E-mail: judith.goris@ugent.be

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Lay abstract

Recent theories propose that autism spectrum disorder (ASD) is characterized by an impairment in determining when to learn and when not. Here, we investigated this hypothesis by estimating learning rates (i.e. the speed with which one learns) in three different environments that differed in rule stability and uncertainty. We found that neurotypical participants with more autistic traits performed worse in a volatile environment (with unstable rules), as they chose less often for the most rewarding option. Exploratory analyses indicated that performance was specifically worse when reward rules were opposite to those initially learned, for participants with more autistic traits. However, there were no differences in the adjustment of learning rates between participants with more versus less autistic traits. Together, these results suggest that performance in volatile environments is lower in participants with more autistic traits, but that this performance difference cannot be unambiguously explained by an impairment in adjusting learning rates.

Abstract

Recent theories propose that autism spectrum disorder (ASD) is characterized by an impairment in determining when to learn and when not. We investigated this by estimating learning rate in environments varying in volatility and uncertainty. Specifically, we correlated autistic traits (in 163 neurotypical participants) with modelled learning behavior during probabilistic reward learning under three conditions: a Stationary Low Noise condition with stable reward contingencies, a Volatile condition with changing reward contingencies, and a Stationary High Noise condition where reward probabilities for all options were 60%, resulting in an uncertain, noisy environment. Consistent with earlier findings, we found less optimal decision-making in the Volatile condition for participants with more autistic traits. However, we observed no correlations between underlying adjustments in learning rates and autistic traits, suggesting no impairment in updating learning rates in response to volatile versus noisy environments. Exploratory analyses indicated that impaired performance in the Volatile condition in participants with more autistic traits, was specific to trials with reward contingencies opposite to those initially learned, suggesting a primacy bias. We conclude that performance in volatile environments is lower in participants with more autistic traits, but this cannot be unambiguously attributed to difficulties with adjusting learning rates.

Introduction

Autism spectrum disorder (ASD) is one of the most common neurodevelopmental disorders, and is characterized by persistent deficits in social communication and interaction, as well as restricted, repetitive patterns of behavior (American Psychiatric Association, 2013). Some have hypothesized that impairments in (implicit) learning might play a role in explaining these symptoms. However, the literature on implicit learning deficits in ASD has produced mixed results, with some studies showing intact (Barnes et al., 2008; Brown, Aczel, Jiménez, Kaufman, & Grant, 2010; for a meta-analysis, see Foti, De Crescenzo, Vivanti, Menghini, & Vicari, 2015), and others impaired implicit learning (Costescu et al., 2015; D'Cruz et al., 2013; Solomon et al., 2011; South et al., 2012). Recent predictive coding theories on ASD have tried to shed new light on these conflicting findings (Lawson et al., 2014; Palmer et al., 2017; Van de Cruys et al., 2014, 2017). Specifically, according to these accounts, people with ASD do not experience difficulties with learning per se, but are less efficient in determining when to learn and when not. In the current paper, we aimed to investigate this key hypothesis using a computational model that allows us to evaluate contextual differences in learning rate (i.e., the speed with which one learns).

According to the predictive coding framework, the brain constantly makes predictions about the world and processes sensory input in light of those predictions (Friston, 2010; Rao & Ballard, 1999). When incoming information deviates from what is expected, the brain experiences a *prediction error*, which can be used to signal that future predictions should be adapted. Importantly, however, our brain also needs to distinguish between relevant and irrelevant prediction errors based on contextual information, as some prediction errors can indicate that there is learnable information in the environment, while others signify merely noise

and can be ignored (e.g., Sarafyazd & Jazayeri, 2019; Yu & Dayan, 2005). Therefore, our brain needs to know when to learn more from prediction errors, and when not (or only cautiously), resulting in higher or lower learning rates, respectively. In ASD, specifically this flexible weighting of prediction errors (sometimes referred to as *precision*) is thought to be impaired. In other words, it has been argued that individuals with ASD are less efficient in detecting in which context a surprising signal is important (e.g. because underlying rules have changed, i.e. volatility) and in which it is not (e.g. because it is just noise) (Lawson, Rees, & Friston, 2014; Van de Cruys et al., 2014; Van de Cruys, Van der Hallen, & Wagemans, 2017; for a review, see Palmer, Lawson, & Hohwy, 2017). While different theories put forward different mechanisms for this alteration (weaker predictions, Pellicano & Burr, 2012; attenuated prior precision, Lawson et al., 2014; overall high precision of sensory prediction errors, Van de Cruys et al., 2014), they converge on the idea that individuals with ASD have difficulties with distinguishing between more important and less important surprise signals. A recent study found support for this hypothesis, by showing that early sensory prediction error signals in the brain are less modulated by context in an ASD group, compared to a control group (Goris et al., 2018). However, it could not be evaluated whether this lower context-sensitivity was directly related to an impairment in adjusting learning rates in ASD. Specifically, we hypothesize that this less flexible updating of prediction errors in ASD should also be reflected in a suboptimal adjustment in learning rate depending on different environments.

Several studies already investigated learning in probabilistic environments in ASD, but mostly focused on whether subjects with ASD (or more autistic traits) were able to learn in the first place. The results have been mixed. For example, Robic, Sonié, Fonlupt, Henaff, Touil and colleagues (2015) found in a probabilistic reward learning task that participants with ASD were

less likely than typically developed (TD) participants to meet a 60% success criterion in a volatile context (i.e. with changing reward probabilities), while there was no difference in a stable context. However, it remains unclear what exactly caused the difference between both groups in this study. Later studies explicitly calculated a learning rate parameter. For example, Manning, Kilner, Neil, Karaminis and Pellicano (2017) investigated learning rates in children with ASD during a probabilistic reward learning task with both a stable and volatile condition. In contrast to their expectations, they did not find any differences with typically developing participants. Later, Lawson, Mathys and Rees (2017), estimated learning rates in a perceptual learning task with a hierarchical model. They found that adults with ASD had the tendency to attribute uncertainty more to environmental volatility, in comparison with a control group who attributed uncertainty more to probabilistic noise. This indeed suggests that individuals with ASD are less efficient in distinguishing volatility (i.e. learnable changes in underlying reward contingencies) from probabilistic noise. Finally, Crawley and colleagues (2019) also found general differences in learning rate in a probabilistic reversal learning task (which did not include a volatile condition) in persons with ASD. They observed generally elevated learning rates in children and adults with ASD (but not in adolescents), consistent with theories proposing an overall higher tendency to update predictions in response to prediction errors (Van de Cruys et al., 2014). Importantly, most of these previous studies only contrasted two conditions: one with more, and one with less volatile contingencies. However, none of these previous studies directly compared learning rates in conditions with volatile contingencies versus noise (i.e., no contingencies), and thus leave open the question whether or not ASD is associated to an inability to dissociate volatile environments from noise.

Therefore, in the present study, we used a probabilistic reward learning task that contrasts a volatile environment with changing reward contingencies on the one hand, to a very noisy environment with no changing reward contingencies on the other (Kennerley et al., 2011; Silvetti et al., 2013). Specifically, in this task, participants are instructed to choose between different pictures, which can either lead to reward or not, and are told that the reward probabilities of the pictures can change over time. In the Stationary Low Noise condition, the reward probabilities of the pictures remain stable. In the Volatile condition, the reward probabilities switch every 18 trials (on average). Crucially, there is also a third Stationary High Noise condition, where the reward probabilities also stay stable but reward probabilities for all pictures are fixed at 60%. This means that many prediction errors remain, resulting in a very uncertain, noisy condition. A previous study using this paradigm already showed that learning rate was lower in the Stationary Low Noise and Stationary High Noise condition, compared to the Volatile condition (Silvetti et al., 2013).

Here, we administered this paradigm in a large sample of neurotypical participants, while measuring autistic traits. ASD is considered a clinical condition, but it has been suggested that autistic traits are continuously distributed across the general population (Constantino & Todd, 2003). In line with this assumption, previous studies in the neurotypical population have shown that correlational approaches can produce relevant insights about ASD (Goris et al., 2017; Grinter et al., 2009; Robertson & Simmons, 2013; Stewart & Austin, 2009; Walter et al., 2009).

If ASD is indeed related to an impairment in distinguishing volatility from noise (Palmer et al., 2017; Van de Cruys et al., 2014, 2017), then we specifically expect a smaller difference in learning rate between the Volatile condition and the Stationary High Noise condition in participants with more autistic traits. If, however, ASD is related to an overall higher tendency to

update predictions in response to prediction errors (e.g., Crawley et al., 2019), we would expect to see an overall higher learning rate in participants with more autistic traits, independent of learning condition. Finally, if learning rate is suboptimal in the Volatile condition, we can also expect that participants with more autistic traits would choose the optimal reward option less often in this condition specifically, which would also be in line with the observations of Robic and colleagues (2015).

Methods

All data can be found on the open science framework (<https://osf.io/f4bq2>).

Participants

A power analysis indicated that to detect a Pearson's r correlation of .2 or higher with a one-tailed significance test at $p = 0.05$ and a power of 80%, we need 153 participants. We recruited 186 participants from the Ghent University student population, of which 21 participants were excluded (11 participants for a technical problem during data collection, 7 due to accuracy scores significantly below chance level in the Stationary Low Noise condition, and 3 for inconsistent scores on the ASD questionnaires, see below). Thus, the final sample size was $n = 165$. Seventy-four (45%) of them participated in exchange for course credits and the other 91 (55%) were paid €10 for their participation. Hundred and twenty-three (75%) were female and 26 (16%) were left-handed. Age ranged from 17 to 49 ($M = 22$, $SD = 4$). Sample sizes for the correlational analyses with the ASD questionnaires is $n = 163$, due to missing data in the questionnaires. All participants signed an informed consent before participation.

Experimental Task

Participants were presented with the probability tracking task developed by Silvetti and colleagues (2013), see Figure 1. In this task, participants were instructed to choose between two pictures on each trial (using the Q and W buttons for the left and right figure respectively, on a standard QWERTY keyboard). The pictures belonged to two sets, each including two pictures (i.e. four pictures in total). Each picture set had a specific probability of reward. Participants' goal was to discover by trial and error which pictures were the most rewarding. They were informed that two pictures would frequently lead to reward and the other two only seldom, and that the “good” pictures could become “bad” over time and vice versa. The five participants with the highest scores received a shopping coupon of € 30.

The reward probabilities of each picture set were manipulated in three conditions. In the Stationary Low Noise condition, one set had a reward probability of 70% and the other 30%. In the Stationary High Noise condition, both sets were rewarded in 60% of the trials. In both Stationary conditions, the probabilities remained stable throughout this phase. In the Volatile condition, the reward probabilities were 90% and 10% but switched on average every 18 trials (meaning that the set with a 90% reward probability would get a 10% reward probability and vice versa), resulting in five blocks in the Volatile condition, the first of which had reward contingencies opposite to those in the Stationary Low Noise condition (see Figure 1C).

The experiment started with a familiarization phase of 90 trials of the Stationary Low Noise condition. Next, the three conditions were presented in a random order. Each condition included 90 trials. Total duration of the experiment was approximately 40 minutes (360 trials). To match the reward rate of the Stationary Low Noise condition with those of the other two conditions, 11% of the trials contained both pictures from the low reward probability set.

Figure 1. Overview of the Probability Tracking Task. **(A)** Schematic overview of one trial. The yellow line indicated the participants' choice. Presentation time of fixation cross and choice indication was jittered. **(B)** Picture sets. Each set included two pictures, and was assigned a specific reward probability. **(C)** The reward probabilities for each picture set in the different conditions. Conditions were presented in a random order. In the Volatile condition, reward probabilities switched on average each 18 trials. The experiment started with a familiarization phase of 90 trials of the Stationary Low Noise condition. Figure adapted from Silvetti, Seurinck, van Bochove, & Verguts (2013).

Questionnaires

Two self-report adult ASD questionnaires were used: the Autism-Spectrum Quotient (AQ) and the Social Responsiveness Scale - Adult version (SRS-A), both in Dutch.

Autism-Spectrum Quotient

The AQ is the most well-known questionnaire for measuring autistic traits (Baron-Cohen et al., 2001; Dutch version: Hoekstra, Bartels, Cath & Boomsma, 2008). It consists of 50 items, divided in five subscales of 10 items each: communication, social skills, imagination, attention to detail, and attention switching. The items need to be answered on a 4-point Likert scale (“definitely agree”, “slightly agree”, “slightly disagree”, “definitely disagree”).

Social Responsiveness Scale-Adult Version

The SRS-A measures social symptoms of ASD (Constantino et al., 2003; Dutch version: Noens, De la Marche & Scholte, 2012). It consists of 65 items divided in four subscales: social awareness, social communication, social motivation, and rigidity and repetitiveness. The items are answered on a 4-point Likert scale (“never true”, “sometimes true”, “often true”, “always true”).

Inconsistent Scores

The scale used in the AQ is opposite from that in the SRS-A, meaning that a score of “1” in the AQ means “definitely agree”, while it means “never true” in the SRS-A. We suspected some participants might have used the scales in a wrong way, because some participants had a very high total score on one questionnaire but a very low total score on the other. To identify these participants, we selected eight items that were highly similar in both questionnaires and compared responses to these items. Participants that had a difference of two or more points on at least five of these eight questions were excluded. This resulted in exclusion of three participants. For a similar approach, see Goris, Brass, Cambier, Delplanque, Wiersema, and Braem (2019).

Data analysis

Principal Components Analysis on Questionnaire Scores

Because we did not have differential hypotheses for the two questionnaires, we ran an unrotated Principal Components Analysis (PCA) on the total scores of the AQ and SRS-A, similar to Goris, Brass, Cambier, Delplanque, Wiersema, & Braem (2019). This way, we extracted a single underlying factor for autistic traits, allowing us to simplify the interpretation of the correlational analyses. This factor explained 76% of the total variance of the AQ and SRS-A

scores. Correlations between performance and the AQ and SRS-A separately can be found in the Supplemental Material.

Learning Rate Estimation

We used three different models to estimate learning rates, model A, B and C. For the first two models (A and B), learning rates of the different conditions were estimated by fitting choices of individual participants with a Rescorla Wagner-Softmax selector system (Behrens et al., 2007; Silvetti et al., 2013). The learning rate of the reinforcement learning agent was estimated by Maximum Likelihood Estimation (MLE). *Model A* was similar to the model used in Silvetti and colleagues (2013), which included three parameters for learning rate (for each of the three conditions), and one parameter for temperature, which was fixed across conditions. The temperature parameter estimated the exploration vs. exploitation trade-off. Notably, this model contained the two picture sets as the response options, and thus did not differentiate between the two pictures within a set; this can be considered as a sort of “model-based” behavior, in the sense that reward probabilities are estimated based on the sets. In other words, reward probability for one picture can be estimated based on experience with the other picture within the same set. Model-free behavior on the other hand would entail that reward probabilities for a certain picture are estimated through experience with each specific picture only. To investigate to what extent participants grouped the four pictures into two sets as a measure of model-based versus model-free behavior, we added a parameter gamma in *model B*. Gamma remained fixed across conditions and could vary between 0 and 1, with a value of 0 meaning completely model-free behavior (pictures treated as 4 independent response options) and a value of 1 meaning model-based behavior (pictures grouped into two sets) (Kool et al., 2016). Finally, *Model C* was a simplified version of the Reinforcement Meta Learner (RML) model (Silvetti et al., 2018), from

which we adopted exclusively the algorithm relative to learning rate optimization. In this model, learning rate is dynamic, i.e. changing on a trial-by-trial basis, and this adaptation process is regulated by a meta-learning parameter, influencing the sensitivity to volatility. Specifically, a lower meta-learning parameter in this model would be consistent with a lower threshold of volatility detection and, as a result, a faster adaptation of learning rate to changed volatility conditions. Like for models A and B, model C implemented a Softmax action selector. Thus, fitting model C implied the optimization of two free parameters: meta-learning and temperature, which were both fixed across conditions. Consistent with previous studies (Behrens et al., 2007; Silvetti et al., 2013), in our data analysis, we excluded the first 20 trials of each condition in order to rule out learning rate modulation due to the switch of contingencies between conditions. However, the results did not change in a statistically significant way when all trials were included (except in one case, which is indicated in the Results).

Results

Task Performance

Task performance over time is plotted in Figure 2A. On average, participants made the optimal choice (i.e. the option with the highest probability of reward) in 67% of trials ($SD = .13$) in the Stationary Low Noise condition, which was significantly more than in the Volatile condition ($M = 64\%$, $SD = .13$), $t(164) = 2.31$, $p = .02$, $d = 0.18$. In the Stationary High Noise condition, there was no optimal choice as both options had the same reward probability.

Questionnaires

Scores on the AQ ranged from 67 to 168 ($M = 103.16$, $SD = 18.21$). With binary scoring, scores ranged from 2 to 40 ($M = 15.42$, $SD = 7.62$). Eight out of 165 participants (5%) binary scores were between 26 and 32, hinting at mild ASD (Woodbury-Smith et al., 2005). Seven participants (4%) had a binary score above 32, possibly suggesting ASD (Baron-Cohen et al., 2001). Cronbach's alpha was 0.89 for the AQ, indicating good internal consistency. SRS-A total raw scores ranged from 8 to 118 ($M = 40.17$, $SD = 18.96$). Twenty out of 163 participants' scores (12%) indicated mild to moderate deficiencies in social responsivity. Two participants (1%) had a score indicating severe deficiencies in social responsivity. Cronbach's alpha for the SRS-A was 0.76 which indicates acceptable internal consistency. AQ and SRS-A scores correlated positively, $r = .51$, $p < .001$, which confirms the construct validity of both measures. In what follows, we will discuss the results regarding the PCA factor scores that were extracted from the total scores of the AQ and SRS-A, as we did not have differential hypotheses for the two questionnaires (see Method).

Relation between Performance and Autistic Traits

In Figure 2A, mean performance over time is plotted, as well as separately for participants with less and more autistic traits, based on a median split of the PCA factor scores. In our analyses, however, we treated PCA factor scores as a continuous variable instead of a binary one, using Pearson correlation coefficients (but similar results were obtained when using Spearman correlations). We observed no correlation with performance in the Stationary Low Noise condition, $r = .02$, $p = .80$. However, performance in the Volatile condition correlated significantly with the PCA factor score, $r = -.20$, $p = .01$, indicating that participants with more autistic traits showed less optimal decision making in the Volatile condition, see Figure 2B. The Bayes Factor for the correlation between performance in the Volatile condition and PCA factor score (calculated one-sided in line with our unidirectional hypothesis, with a beta prior width of 1) was $BF_{10} = 4.70$, indicating substantial evidence for the alternative hypothesis (Jeffreys, 1961). The difference in performance between the Stationary Low Noise and Volatile condition also correlated significantly with the PCA factor, $r = -.18$, $p = .03$, $BF_{10} = 2.30$. Correlations between performance and the AQ and SRS-A separately can be found in the Supplemental Material. As there was no optimal reward decision in the Stationary High Noise condition, we could not compute a correlation with performance in this condition.

Figure 2. Relation between performance and autistic traits. (A) Mean performance over trials, separately for individuals with less autistic traits (below median on Principal Components Analysis (PCA) factor score) in light blue, and individuals with more autistic traits (above median on PCA factor score) in dark blue. The black line represents the mean of all participants. In the Volatile condition, the dotted lines represent the trial number at which the reward probabilities of the sets changed. For the Stationary High Noise condition, there was no optimal choice as both options had the same reward probability. (B) Correlation between performance in the Volatile condition and the PCA factor scores. The trend line reflects the significant, negative Pearson correlation coefficient.

Relation between Learning Rates and Autistic Traits

Next, we turned to an analysis of the model parameters, to study which parameters could potentially explain the suboptimal decision making in the Volatile condition in people with more autistic traits. As mentioned before, model A estimated three learning rates for each condition separately, and temperature. Model B additionally included a gamma parameter, estimating to which extent participants grouped the stimuli into two sets. Model C had a dynamic learning rate and included two parameters: meta-learning and temperature. The Bayesian Information Criterion (BIC) values were 261 for model A, 260 for model B and 259 for model C. Lower BIC values represent a better model fit, meaning that model C fit the data best.

Model A

Learning rate was investigated with a repeated-measures analysis of covariance (ANCOVA) including condition as a within-subjects factor (3 levels: Stationary Low Noise, Stationary High Noise and Volatile) and standardized PCA factor scores as a covariate. Mean learning rates per condition are plotted in Figure 3A, as well as learning rates separately for participants with less and more autistic traits, based on a median split of the PCA factor scores. Importantly, in our analyses we included PCA factor score as a continuous variable instead of a binary one.

Learning rate was significantly modulated by condition, $F(2, 320.63) = 42.27, p < .001$ (Greenhouse-Geisser corrected), $\eta_p^2 = 0.36$, with follow-up t-tests indicating a significant difference between the Stationary Low Noise and Stationary High Noise condition, $t(164) = -3.53, p < .001, d = 0.27$, as well as between the Stationary High Noise and the Volatile condition, $t(164) = -5.49, p < .001, d = 0.43$. There was no main effect of PCA factor score on learning

rate, $F(1, 161) = 0.46$, $p = .50$, $\eta_p^2 = 0.003$, see Figure 3B, in contrast with earlier observations of an overall higher learning rate in ASD¹. In fact, the one-sided Bayes factor (where the alternative hypothesis is a higher learning rate for higher factor scores, cf. Crawley et al., 2019) for this relation was $BF_{01} = 16.20$, indicating strong evidence for the null hypothesis. Crucially, there was no interaction effect between PCA factor scores and condition, $F(2, 320.63) = 0.38$, $p = .68$ (Greenhouse-Geisser corrected), $\eta_p^2 = 0.005$, suggesting that the differences in learning rate between conditions were not influenced by autistic traits. When investigating the relation between the difference in learning rate between the Volatile and Stationary High Noise condition and the PCA factor score more specifically, we did not find a correlation, $r = -.07$, $p = .40$, $BF_{01} = 4.53$, suggesting substantial evidence for the null hypothesis, see Figure 3C. Contrary to our hypothesis, this indicates that autistic traits were not related to an impairment in adjusting learning rates to different learning environments. Finally, there was no correlation between temperature and PCA factor score, $r = .10$, $p = .22$.

¹ When all trials were included in the model, there was a significant effect of PCA factor scores on learning rate, $F(1, 161) = 4.47$, $p = .04$, $\eta_p^2 = .03$, but the direction was opposite to earlier findings, indicating lower learning rates for participants with more autistic traits.

Figure 3. Relation between learning rates in model A and autistic traits. **(A)** Learning rates per condition, separately for individuals with less autistic traits (below median on Principal Components Analysis (PCA) factor score) and more autistic traits (above median on PCA factor score). Error bars reflect the standard error of the mean (SEM). **(B)** Absence of a correlation between PCA factor score and average learning rate. **(C)** Absence of a correlation between PCA factor score and difference in Learning Rate between the Volatile and Stationary High Noise condition. Trend lines reflects the non-significant Pearson correlation coefficients.

Model B

The same statistical tests on the learning rates in model B resulted in highly similar statistical findings. First, learning rate was also significantly modulated by condition, with significant differences between the three conditions (all $p < .01$). Next, there was also no main effect of PCA factor score on learning rate, $F(1, 161) = 2.59, p = .11, \eta_p^2 = 0.02$, one-sided $BF_{01} = 25.67$. Again, there was no interaction effect between PCA factor score and condition, $F(2, 321.09) = 1.85, p = .16$ (Greenhouse-Geisser corrected), $\eta_p^2 = 0.02$. For the difference in learning rate between the Volatile and Stationary High Noise condition and the PCA factor score specifically, we did not find a significant correlation, $r = -.10, p = .23$, one-sided $BF_{01} = 2.80$. Finally, there were no significant correlations between temperature and PCA factor score, $r = .08, p = .33$, or between gamma and PCA factor score, $r = -.07, p = .39$.

Model C

Both models A and B did not show a relation with learning rate (or any other parameter). For this reason, we also tried fitting a third model C, which allows learning rate to vary on a trial-by-trial basis (See Figure 4²) and estimates a meta-learning parameter to determine how much learning rate adapts to changing volatility. This way, rather than having to calculate the difference in learning rate between different conditions, we can evaluate our hypothesis that people with more autistic traits have problems regulating learning rate using only one parameter.

² As can be seen in Figure 4, learning rate seems to stop increasing towards the end of the Volatile condition for participants with more autistic traits. However, when we conducted an ANCOVA on learning rate with block as within-subjects factor (5 levels: 1, 2, 3, 4 and 5) and PCA factor score as covariate, there was no interaction between block and PCA factor score, $F(4, 425.35) = 1.26, p = .29$ (Greenhouse-Geisser corrected), $\eta_p^2 = 0.03$. This indicates no relation between PCA factor score and the evolution of learning rate over time.

Importantly, there was neither a significant correlation between meta-learning and PCA factor score, $r = .07$, $p = .41$, nor between temperature and PCA factor score, $r = .08$, $p = .29$. In accordance with the analyses of models A and B, we also ran an ANCOVA on learning rate (averaged over trials) with condition as a within-subjects factor (3 levels: Stationary Low Noise, Stationary High Noise and Volatile) and standardized PCA factor scores as a covariate. This ANCOVA again showed a significant effect of condition, $F(2, 311.22) = 84.84$, $p < .001$ (Greenhouse-Geisser corrected), $\eta_p^2 = 0.47$, which indicated a significant difference between the Stationary High Noise and Volatile condition, $t(164) = 10.52$, $p < .001$, $d = 0.82$, but not between the Stationary Low Noise and Stationary High Noise condition, $t(164) = 0.51$, $p = .61$, $d = 0.04$. There was again no main effect of PCA factor scores, $F(1, 161) = 0.60$, $p = .44$, $\eta_p^2 = 0.004$, and no interaction between condition and PCA factor scores, $F(2, 311.22) = 1.60$, $p = .20$ (Greenhouse-Geisser corrected), $\eta_p^2 = 0.02$. Similarly, when focusing on the difference in learning rate (averaged over trials) between the Volatile and Stationary High Noise condition, we again did not find a significant correlation with the PCA factor score, $r = -.13$, $p = .11$.

Figure 4. Average learning rates over time in Model C, separately for individuals with less autistic traits (below median on Principal Components Analysis (PCA) factor score) and more autistic traits (above median on PCA factor score). In the Volatile condition, the dotted lines represent the trial numbers at which the reward probabilities of the sets changed. There was no interaction effect between PCA factor score and condition (Stationary Low Noise, Stationary High Noise, Volatile) on average learning rate. Although it looks like there might be an effect of PCA factor score on learning rate in the last two blocks of the Volatile condition, a targeted correlational analysis on only these trials did not show a statistically significant correlation between PCA factor score and learning rate.

Initial vs. secondary reward contingencies in the Volatile condition

Because we did not find a relation between autistic traits and any of the model parameters in models A, B and C that could explain the relation with performance, we investigated the performance results in more detail by looking at performance depending on the different reward contingencies during the Volatile condition.

As can be seen in Figure 2A, performance for participants with more autistic traits seems to be specifically decreased in blocks 1, 3 and 5 from the Volatile condition. These were the blocks in which reward contingencies were opposite to those in the familiarization phase, while blocks 2 and 4 had the same reward contingencies as the familiarization phase (see Figure 1C). Indeed, performance in blocks 1, 3 and 5 was differently related to PCA factor score than performance in blocks 2 and 4, as indicated by an interaction between PCA factor score and block type (2 levels: 1, 3 and 5 combined versus 2 and 4 combined) in an ANCOVA on performance, $F(1, 161) = 7.89, p = .006, \eta_p^2 = .05$. Follow-up correlational analyses showed a significant negative correlation between PCA factor score and performance in the blocks with the opposite reward contingency (blocks 1, 3 and 5), $r = -.24, p = .002$, but not with performance in the blocks with the initial reward contingency (blocks 2 and 4), $r = .03, p = .75$. This seems to suggest that individuals with more autistic traits have specific difficulties in applying contingencies opposite to those they learned at the beginning of the experiment.

We explored these findings further by investigating learning rates in blocks with initial vs. opposite reward contingencies. To this end, we used model C as this was the only model estimating trial-by-trial learning rates, and thus allowed to compare learning rates in different blocks of the Volatile condition. The difference in learning rates between these two block types (blocks 1, 3 and 5 combined minus blocks 2 and 4 combined) indeed correlated marginally

significantly with PCA factor score, $r = .13$, $p = .092$ This suggests that participants with more autistic traits might increase their learning rate when (re)learning about the initial reward contingencies in comparison to blocks with opposite reward contingencies, as compared to participants with lower autistic traits. However, this exploratory, marginally significant finding needs to be interpreted with caution.

Discussion

Recent predictive coding theories have proposed that ASD might be characterized by an impairment in determining when to learn and when not (Lawson et al., 2014; Palmer et al., 2017; Van de Cruys et al., 2014, 2017). This idea could shed new light on the conflicting findings in implicit learning in ASD (e.g. Brown et al., 2010; Costescu et al., 2015; Foti et al., 2015; South et al., 2014), and has inspired several studies to investigate learning in probabilistic environments in ASD (Lawson et al., 2017; Manning et al., 2017; Sevgi et al., 2019). However, until now it was never directly investigated whether learning in ASD is characterized by an inability to dissociate between volatile environments and noise, which is a key hypothesis of predictive coding theories of learning in ASD. In the current study, we compared learning rates (i.e. the speed with which one learns) in response to volatility versus noise, using a correlational approach with ASD questionnaires. To this end, we used a probabilistic reward learning task with three conditions: a Stationary Low Noise condition in which reward probabilities remained stable, a Volatile condition in which reward probabilities changed regularly, and crucially, a Stationary High Noise condition where reward probabilities for all options were fixed at 60%, resulting in an uncertain, noisy environment.

First, our findings show that participants with more autistic traits perform worse in the Volatile (but not the Stationary) condition, i.e. they choose less frequently for the option with the highest probability of reward. This adds to a growing body of evidence that there is a specific performance deficit in learning under volatile environments in ASD. For example, Robic and colleagues (2015) found that participants with ASD were less successful in a volatile context, while there was no group difference in a stable context. Similarly, Sevgi and colleagues (2019) also found lower performance for probabilistic learning about a social cue in ASD in both stable

and volatile contexts, but the difference with the control group was larger in the volatile context. A deficit with probabilistic learning in volatile environments would be predicted by recent predictive coding theories of learning in ASD, as they propose an impairment in dissociating uninformative noise (stemming from probabilistic feedback) from informative volatility (indicating changed task rules). To investigate this hypothesized underlying mechanism in more detail, we modelled learning rates in the different conditions.

Surprisingly, we did not find a clear relation between learning rates and autistic traits. First, there was no generally elevated learning rate in participants with more autistic traits, which is consistent with the results of Manning and colleagues (2017), but not with the elevated learning rates in ASD found by Crawley and colleagues (2019). If anything, we observed a hint towards generally lower learning rates with more ASD symptoms, as seen in model A when all trials were included. However, we have to be careful when interpreting this result, as this was not replicated applying model B or C, and disappeared when the first 20 trials were excluded in model A (as also done in previous studies, Behrens et al., 2007; Silvetti et al., 2013). Still, these results do provide evidence against a generally elevated learning rate in ASD. While one predictive coding account originally put forward a generally higher learning rate in ASD (Van de Cruys et al., 2014), most evidence points towards no overall higher precision of prediction errors (Chambon et al., 2017; Gonzalez-Gadea et al., 2015; Goris et al., 2018; Skewes et al., 2014), which seems consistent with our results.

Most importantly, we hypothesized an impairment in dissociating volatility from noise in participants with more autistic traits, but did not find any differences in learning rates between conditions as a function of autistic traits. Model C (which was the model best fitting the data) included a meta-learning parameter specifically controlling the learning rate adaptation to

changes in volatility, but this meta-learning parameter did not correlate with autistic traits. This is not in line with the results of Lawson and colleagues (2017), which showed a difference between participants with and without ASD in a higher-order learning rate estimating learning about volatility. However, we have to be cautious when comparing these findings, as Lawson and colleagues looked at perceptual decision-making instead of reward learning, with a clinical sample instead of a correlational design. Moreover, the difference in learning rate between the Volatile and Stationary High Noise condition was not smaller in participants with more autistic traits, contrary to our main hypothesis that learning rates would differ less between probabilistic noise and environmental volatility in ASD.

A post-hoc, exploratory analysis indicated that the difference in performance may be driven by specific difficulties in the blocks where reward contingencies were opposite to those learned in the beginning of the experiment, which can be seen as an increased *primacy bias*. This is consistent with findings of lower performance following task rule reversal (D'Cruz et al., 2013; South et al., 2012). In line with this, the only hint we found for an atypical modulation of learning rate in participants with more autistic traits, was the differential adaptation in learning rate in response to initial vs. secondary reward contingencies in the Volatile condition. This suggests that participants with more autistic traits are more eager to revert back to, and (re)learn, initial reward contingencies in comparison to secondary reward contingencies, as compared to participants with lower autistic traits. However, this relation was only marginally significant, unexpected, and our model was not set up to specifically capture differences in learning rate in response to these two different reward contingencies. Therefore, we have to interpret this finding with great caution.

In sum, we did not find a clear relation between autistic traits and learning rates in the current study. This might suggest that the inflexible weighting of prediction errors as proposed by predictive coding theories of ASD, is only apparent during low-level sensory processing (Goris et al., 2018; Palmer et al., 2017; Pellicano & Burr, 2012), but does not transfer directly to higher-level processes, such as learning rates during decision-making based on reinforcement learning.

Notably, while we could not unambiguously capture the differences in behavior with our estimations of learning rate, the other model parameters, temperature, gamma (in model B) and meta-learning (in model C), also did not correlate with autistic traits. This could imply that their model-free algorithms might not be sufficient to unravel the impairments associated with ASD that lead to their suboptimal choice behavior in volatile conditions. Although model B could be considered “model-based” to some extent, in that it tried to account for the grouping of similar stimuli, all three models learned via trial and error without learning about the structure of the task or the environment. For example, their algorithms neither learn about the probability that reward contingencies might change (i.e., transition probabilities), nor do they have separate memories for initially vs. later learned reward contingencies. More advanced model-based learning approaches might be better suited to explain the mechanisms behind these impairments. For example, one interesting avenue to explain decision making in ASD could be to use models that retain memory of initial versus later learned reward contingencies separately (e.g. Gershman, Monfils, Norman, & Niv, 2017; Verbeke & Verguts, 2019). Another interesting direction could be to include additional performance measures (such as reaction times), instead of only choice behavior (Ballard & McClure, 2019; Pedersen et al., 2017). At this point, we believe that sharing the null results of our models is just as important, as these show that the

performance difference cannot be unambiguously related to differences in learning rate as included in model-free approaches, which are most often used to capture behavior in reward decision making paradigms (Behrens et al., 2007; Silvetti et al., 2013). We encourage future researchers to try and model our data (which can be found online on osf.io/f4bq2) using other models.

Finally, correlational studies in the neurotypical population might suffer less from confounding factors such as comorbidities and medication, in comparison to clinical studies, and allow for high statistical power. Previously it has been shown that this type of studies can lead to relevant insights about ASD (Goris et al., 2017; Grinter et al., 2009; Robertson & Simmons, 2013; Stewart & Austin, 2009; Walter et al., 2009). Nonetheless, it remains possible that participants with an official ASD diagnosis do show more marked differences in learning rates. Therefore, further research in clinical samples is warranted.

In conclusion, we investigated whether learning rates differed less between volatile versus noisy environments in people with more autistic traits, as proposed by recent predictive coding theories of ASD. While we did observe lower task performance in volatile environments for participants with more autistic traits, there were no clear associations between autistic traits and the estimated learning rates. Therefore, we did not find evidence for the proposed impairment in dissociating volatile environments from noise in ASD. Exploratory analyses indicated that performance in participants with more autistic traits was specifically worse when reward contingencies were opposite to those initially learned, suggestive of a heightened primacy bias in autism, which is an interesting direction for future research. In sum, our results show that performance in unstable, probabilistic learning tasks is lower in people with more autistic traits,

but that this performance difference cannot be unambiguously attributed to an impairment in (the modulation of) learning rate.

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Supplemental Material

Supplemental Table 1. Pearson's correlation coefficients r for the correlations between performance in the different conditions and the subscales of the Autism Spectrum Quotient (AQ) and the Social Responsiveness Scale – Adult version (SRS-A). Correlations are shown with performance in the Stationary Low Noise condition and the Volatile condition, as well as with the difference in performance between these two conditions. The full names of the subscales can be found in the methods section. Please note that the significance levels are not corrected for multiple comparisons: * $p < 0.05$, ** $p < 0.01$, *** $p < .001$

	AQ total	AQ social	AQ switch	AQ detail	AQ comm	AQ imag	SRS-A total	SRS-A consc	SRS-A comm	SRS-A motiv	SRS-A rigid
Stationary Low Noise	0.06	0.02	0.14	0.06	0.01	-0.01	-0.02	-0.03	-0.04	0.02	0.00
Volatile	-0.18*	-0.16*	-0.26**	-0.09	-0.12	-0.04	-0.17*	-0.17*	-0.15	-0.13	-0.12
Volatile – Stationary Low Noise	-0.19*	-0.14	-0.33***	-0.12	-0.11	-0.02	-0.12	-0.11	-0.09	-0.12	-0.10