Beyond Prior Belief and Volatility:
The Distinct Iterative Prior Updating Process in ASD

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Abstract

Research has shown individuals with autism spectrum disorder (ASD) display atypical patterns in predictive processing, yet it remains controversial regarding what causes these atypical behaviors because findings have been inconsistent. Our study employed a two-state Bayesian model to decide between two suggested factors: an aberrant long-term prior and atypical short-term iterative belief updating. Both ASD individuals and typically developing (TD) counterparts participated in a task where they reproduced time durations over two sessions, one characterized by high volatility and the other by predictable sequences. Both sessions involved the same time durations, but the sequences differed in volatility. While both groups adjusted their prior belief to the level of volatility in a similar manner, they diverged in their short-term iterative updating of beliefs. Individuals with ASD iteratively adjusted their beliefs with each new stimulus as if it were less connected to previous ones compared to TD individuals, thereby assigning greater weight to incoming sensory information. Our findings highlight that the distinctive signature of cognitive processing in ASD lies in a mechanism of overreliance on sensory input specific to short-term iterative belief updating.. This unique characteristic may mirror an experience among individuals with ASD of temporal discontinuity rendering the world overly unpredictable.

keywords: autism, volatility, prior belief, iterative updating

Introduction

Autism Spectrum Disorder (ASD) is marked by difficulties in social skills, communication, and a pattern of repetitive behaviour (APA, American Psychiatric Association, 2013). Research shows that people with ASD often struggle more than their typically developed (TD) counterparts in adapting to situations with overwhelming sensory stimulation (Gernert et al., 2020; Leekam et al., 2007; Tomchek & Dunn, 2007), and they are more sensitive to sensory processing (Mottron et al., 2006; Simmons et al., 2009). This heightened sensitivity correlates with the severity of symptoms (Falter, Elliott, et al., 2012; Falter & Noreika, 2011; Isaksson et al., 2018; Robertson & Baron-Cohen, 2017), and extends to time processing, although the findings on atypical performance remain mixed (Casassus et al., 2019; Falter, Noreika, et al., 2012; Isaksson et al., 2018). Over the past decade, multiple theories have emerged that employ predictive processing and Bayesian framework to account for these sensory atypicalities in autism (Cannon et al., 2021; Lawson et al., 2014, 2017; Palmer et al., 2017; Pellicano & Burr, 2012; Sinha et al., 2014; Van de Cruys et al., 2014). The Bayesian framework posits that our actions and perception aim to continually refine-tune our predictions and minimize prediction errors. It suggests that our perception can be better explained by combining sensory inputs and our prior knowledge or experience according to their uncertainty.

While these theories concur that predictive processing is different in ASD, they diverge on the specifics. The “attenuated-prior” model argues that individuals with ASD generally rely less on their internal expectations due to their weakened prior beliefs (Pellicano & Burr, 2012). On the other hand, the “heightened and inflexible precision of prediction errors in Autism” (HIPPEA) theory attributes the sensory atypicalities in ASD to an overemphasis on prediction errors (Van de Cruys et al., 2014). Lawson and colleagues (2014) offer a similar perspective, suggesting that an inability to reduce sensory precision in ASD may tip the scales in favor of sensory inputs over prior beliefs. Despite their conceptual differences, these theories converge on the idea that individuals with ASD tend to prioritize sensory information. This is supported by recent research showing that people with ASD are less swayed by predictable information (Fogelson et al., 2019; Thillay et al., 2016), slower in forming goal-directed anticipations (Ganglmayer et al., 2020), and less reliant on internal

priors when estimating time (Karaminis et al., 2016). This preference for sensory inputs over prior belief has also been evident in research on duration/pitch discrimination (Lambrechts et al., 2018) and perceptual simultaneity (Falter et al., 2013).

Contrary to the notion that ASD impacts the formation of prior beliefs, evidence suggests that many such priors - especially those based on experience or top-down knowledge - remain typical. For instance, performance was found to be typical for learning one-shot priors, such as recognizing a Dalmatian dog camouflaged by black patches (Van de Cruys et al., 2018), responding to gaze cues from preceding trials (Pantelis & Kennedy, 2017; Pell et al., 2016), and using external reference coordinates in tactile spatial tasks (Hense et al., 2019). Such inconsistencies prompted Palmer and colleagues (2017) to question the adequacy of simplistic Bayesian models, which assume a static world. They proposed that the peculiarities in ASD might stem from altered expectations about the uncertainty of changes of hidden states (termed 'meta-volatility') in hierarchical inference. To explore this, Lawson et al. (2017) designed a discrimination task where participants responded to probabilistic cues (either a high or low tone) predicting an upcoming stimulus. They found that individuals with ASD exhibited less variation in response times (RTs) and pupil dilation when faced with expected versus unexpected outcomes. Computational modeling revealed that these individuals experience diminished surprise and heightened sensitivity to uncertainty, leading them to overestimate the volatility of their environment. On the other hand, Manning et al.(2017) found no such differences in a reward-probability learning task (the likelihood of a chest containing a reward) involving children with ASD and matched TD counterparts. Both groups adapted to changing conditions, suggesting that predictive mechanisms impacting perception in ASD may not extend to learning tasks. This aligns with emerging research indicating that ASD is not associated with a generalized learning deficit, but instead atypical management of short-term prediction errors (Allenmark et al., 2021) or updating social expectations, such as other people's intentions (Rosenthal et al., 2019), or context updating (Randeniya et al., 2021).

The way we update priors depends on our expectations about how much variation will occur from one trial to the next (Glasauer & Shi, 2022). For instance, if you expect little change across trials, you are likely to rely more on prior beliefs that you initially learned. On the other hand, if you expect more variability, you may lean more on sensory input for your responses. Glasauer and Shi (2022) argue that these prior beliefs are not static; they evolve

through sequential learning from one trial to another, a process that can also produce a central tendency effect. While TD individuals may share a common global prior, their responses to each trial can vary significantly based on their beliefs about the temporal continuity of the sequence. Up to date, Bayesian inference models in ASD research (Lawson et al., 2014, 2017; Van de Cruys et al., 2014) have primarily centered on differences in final prior beliefs and their subsequent impacts on sensory estimates. A recent review shows that experimental evidence for this compromised prior belief is relatively weak (Angeletos Chrysaitis & Seriès, 2023). These models often overlook the nuances of short-term, iterative updating of prior beliefs from one trial to the next. However, a recent study has shown that in a tone pitch discrimination task, individuals with ASD were less affected by recent events compared to their matched peers, yet they showed a similar magnitude of longer-term contribution (Lieder et al., 2019). Similarly, a study on a finger-tapping synchronization task has also revealed that individuals with ASD struggled to synchronize their movements to external cues, showing a slower adaptation to changes in tempo than their counterparts (Vishne et al., 2021). Therefore, a deeper understanding might be gleaned from exploring how individuals with ASD, as opposed to TD individuals, manage these short-term adjustments and adapt to long-term environmental volatility. Such an investigation could provide pivotal evidence in resolving atypical short-term updating and long-term priors in ASD: is predictive processing in ASD atypical in terms of long-term priors regarding volatility, or in terms of short-term prediction error handling?

For this purpose, the present study was designed to differentiate between these options, employing a duration reproduction paradigm as our methodological tool (Glasauer & Shi, 2021; Karaminis et al., 2016; Shi, Ganzenmüller, et al., 2013). Participants were asked to observe a visual disk that appeared for a certain duration and then replicate that duration by pressing a key (Figure 1a). They completed this task in two different sessions, each featuring the same set of durations but varying the level of volatility (unpredictability) from one trial to the next (depicted in Figure 1b). We expected that participants would form prior beliefs based on the distribution of sample durations from the sessions, as evidenced by the central tendency effect. That is, integrating with the prior belief would likely cause them to overestimate shorter intervals and underestimate longer ones (Glasauer & Shi, 2021; Lejeune & Wearden, 2009; Palmer et al., 2017; Shi, Church, et al., 2013). We hypothesized that if individuals with ASD have an attenuated prior belief, their reproductions will show a weaker

central tendency effect compared to TD individuals. Furthermore, if individuals with ASD are prone to overestimate the environmental volatility (Lawson et al., 2017) and give too much weight to new sensory information in their duration estimates, their central tendency will not adapt as flexibly to changes in volatility as in TD individuals. In contrast, if the primary difference between the two groups is in updating short-term inter-trial sequential beliefs (Allenmark et al., 2021; Lieder et al., 2019; Vishne et al., 2021), we would observe varying patterns of trial-to-trial dependencies through autocorrelation analysis. If this is the case, by applying the two-state Bayesian iterative updating model (Glasauer & Shi, 2022), we can uncover whether the groups differ in how they adjust their beliefs based on recent information.

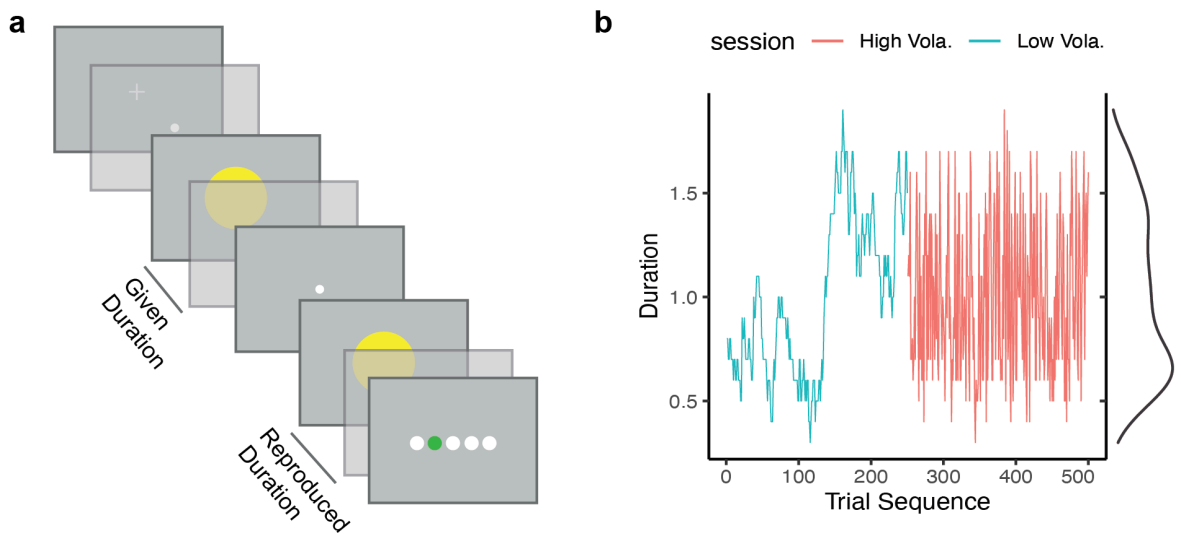

Figure 1. (a) Schematic illustration of a trial sequence used in a duration reproduction task. (**b**) Example duration (trial) sequences in two consecutive 'volatility' sessions. The first session (depicted in cyan) consists of a low-volatility sequence (Low Vola.), and the second session (red) of a high-volatility sequence (High Vola.). Both sessions comprised exactly the same durations (the same density function depicted on the right), differing only in their orders.

Results

Behavioral results

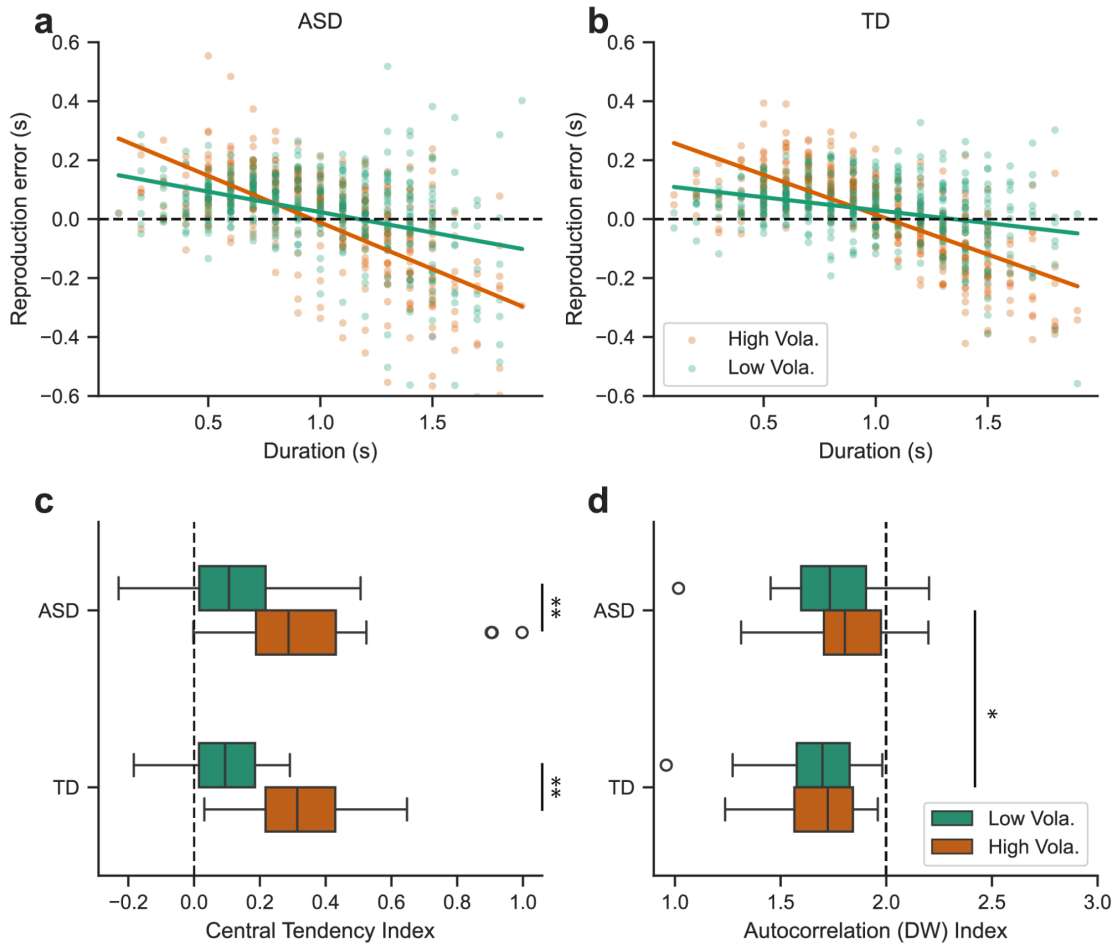

Figure 2. The average reproduction error as a function of the duration for the ASD (**a**) and TD (**b**) groups (each group *n*=32), separated for the high (red) and low (green) volatility sessions. Each individual dot stands for a single participant's mean reproduction error for that given duration. Dots above the horizontal dashed line indicate overestimations and below the line underestimations respectively. Solid lines indicate the fitted trend of the reproduction errors. Notably, the steepness of these fitted trends is higher in high-volatility relative to low-volatility sessions, indicative of stronger central-tendency biases during high volatility conditions. (**c**) The boxplots of the Central Tendency Index (CTI) for both the ASD and TD groups (each group n=32), differentiated according to high and low volatility sessions. A CTI of 0 implies a lack of a central tendency effect, whereas a CTI of 1 suggests a pronounced central tendency effect. The left and right boundaries of the box denote the interquartile range

(IQR), covering the 25th and 75th percentile, while the whiskers indicate 1.5 times the IQR. Three outliers were observed in the ASD group during the high-volatility session. (**d**) The boxplots of the average Durbin-Watson (DW) autocorrelation indices, separated by the high and low volatility sessions, for both the ASD and TD groups. The dashed line, representing a DW value of 2.0, signifies the absence of autocorrelation, while a DW value less than 2 indicates a positive autocorrelation. * denotes $p < .05$, ** $p < .01$.

First, we pre-processed each set of reproduction data, screening for outliers. These outliers were defined as those reproduced durations falling outside the range of [Duration/3, 3×Duration]. Such extreme trials were quite rare, marking up just 0.58% of all trials, and were thus omitted from further analysis.

The average reproduction errors skewed towards overestimation. A mixed ANOVA examining these errors with Volatility and Group as factors revealed that Volatility significantly affected the outcome, $F(1,62) = 5.57$, $p = .021$, $\eta_p^2 = .08$. Specifically, participants overestimated durations more in the low volatility session (by 39 ms) compared to the high volatility session (by 22 ms). Neither the Group factor nor the interaction between Group and Volatility were significant, Fs < 0.698, ps > .4, η_p^2s < .01.

Given the linear approximation characteristic of the central-tendency effect (Glasauer & Shi, 2021; Shi, Church, et al., 2013), we used linear regression to estimate this effect. As seen in Figure 2a and 2b, both the ASD and TD groups exhibit a linear decline in reproduction error with increasing duration, a trend observable in both high and low-volatility sessions. In general, shorter durations were prone to overestimation while longer durations were often underestimated. A steeper linear trend was observed in high-volatility sessions as opposed to the low-volatility ones, suggesting a stronger central tendency bias in the former.

We used the negative slope as the central tendency index (CTI). A CTI of 0 signifies an absence of a central tendency effect, while a CTI of 1 indicates a pronounced central tendency bias. Figure 2c shows the boxplot of the CTI, differentiated by Volatility and Group. A mixed ANOVA, employing Volatility as a within-participant factor and Group as a between-participant factor on CTI, revealed that only the main factor of Volatility was significant, $F(1,62) = 80.11$, $p < .001$, $\eta_p^2 = .56$. Neither the main factor of Group nor the

Volatility × Group interaction showed statistical significance, *F*s < 0.23, *p*s > .63. In the ASD group, there were three outliers who manifested a profound central tendency effect (CTI > 0.9). Essentially, these three outliers reproduced similar durations across all test durations, indicating a strong reliance on prior knowledge in a highly volatile environment and exhibiting a remarkable level of rigidity in their responses (see Appendix 1 the supplementary plot for more detail). Removing these three outliers and their counterparts did not alter the significance: Group, $F(1, 56) = 1.734$, $p = .193$, $\eta_p^2=.03$; Volatility: $F(1, 56) = 81.37$, $p < .001$, $\eta_p^2=.59$; and their interaction, $F(1, 56) = 3.324$, $p = .074$, $\eta_p^2=.056$.

If reproduction errors were solely driven by the central tendency effect, one would expect the residuals to be independent random errors. However, the residuals of the regression analysis revealed a marked differential autocorrelation. Figure 2d shows the average Durbin-Watson (DW) statistics from the regression analysis for two groups, separated into two sessions. The DW statistic is an indicator of the presence of autocorrelation at lag 1, which spans from 0 to 4. A DW of 2 suggests no autocorrelation, and anything less than 2 indicating a positive autocorrelation. A mixed ANOVA revealed that the TD group demonstrated a significantly more positive autocorrelation compared to the ASD group, $F(1,62) = 4.50$, $p = .038$, $\eta_p^2=.07$ (Excluding outliers: $F(1,56) = 8.36$, $p = .005$). Both groups showed the DW being significantly lower than 2 (ASD: 1.78, $t(63) = -7.9$, $p < .001$; TD: 1.68, $t(63) = -11.9$, $p < .001$). This indicates that the simple regression analysis did not fully capture the difference between the two groups, in particular on the inter-trial autocorrelation. However, the main factor of Volatility and the interaction between Volatility and Group failed to reach significance, with *F*s < 2.19, *p*s > .145.

Computational modeling

Our autoregressive analysis indicated that the notable distinction between the two groups likely stemmed from differences in short-term inter-trial updating. To more effectively model this, we adopted the two-state model (Glasauer & Shi, 2022), a hybrid Bayesian iterative updating model that can capture both the long-term central tendency effect and short-term inter-trial sequential dependence. This model posits that an individual's internal belief, or *prior* distribution, is malleable. It evolves through iterative integration of

new sensory information, or *likelihood* distribution, culminating in a revised belief, the *posterior* distribution. From this posterior distribution, one can derive an estimate with a certain cost function (e.g., the maximum a posteriori probability estimate, MAP). Unlike simple iterative Bayesian updating, the two-state model allows for the mean of the posterior distribution to exhibit random variation across trials, rather than a static value. In essence, the new belief for the next trial is sampled from the previous posterior distribution (Figure 3). This two-state model can be described as a Kalman filter process (Glasauer & Shi, 2022), which keeps and updates two states at each step - the predicted duration (x_i) and the mean of the prior belief (m_i):

$$x_i = m_{i-1} + \epsilon_x, \tag{1}$$

$$m_i = m_{i-1} + \epsilon_m, \tag{2}$$

where ϵ_x and ϵ_m are normally distributed noise with variances v and q, respectively. The actual sensory measurement z_i is the updated prediction (x_i), corrupted by the sensory noise $\eta \sim N(0, r)$:

$$z_i = x_i + \eta. \tag{3}$$

The estimate of the state can be rewritten as

$$\hat{x}_i = \widehat{m}_{i-1} + K_1\left(z_i - \widehat{m}_{i-1}\right) \tag{4}$$

$$\widehat{m}_i = \widehat{m}_{i-1} + K_2\left(z_i - \widehat{m}_{i-1}\right) \tag{5}$$

where K_1 and K_2 are the Kalman gains of the predicted duration and the mean of the prior belief, respectively. The Kalman gain K_i is essentially a weighting factor that determines how much weight is given to the sensory input and how much weight ($1 - K_i$) to the prior in light of new prediction error ($z_i - \widehat{m}_{i-1}$). If the Kalman gain is high, the system places more trust in the new information. If it is low, the system trusts more on the previous prediction.

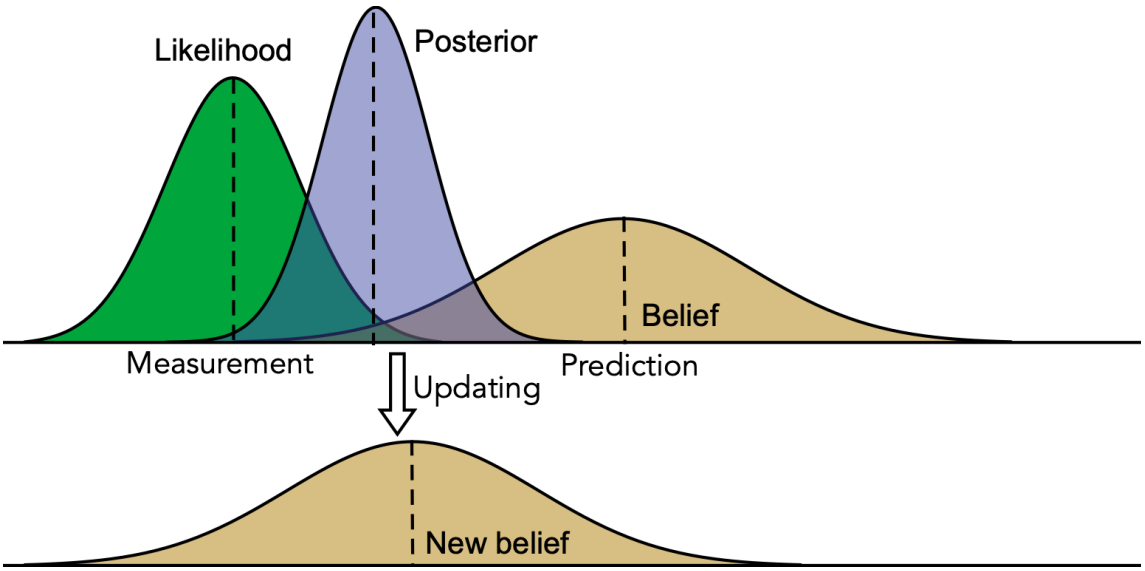

Figure 3. A visual representation of the two-state iterative Bayesian updating model. In trial *n*, the sensory measured likelihood is merged with the existing prior belief (internal prediction of the stimulus) to create a new posterior distribution, which represents the updated belief about the current stimulus (upper panel). A decision is then made from this posterior distribution, guided by a specific cost function, such as the maximum a posteriori probability estimate (MAP). Subsequently, a new prior belief is generated from this posterior, informing the prediction of the subsequent stimulus (lower panel). The two-state model, unlike the standard Bayesian model, allows random variations from the posterior to the new prior belief.

To ensure that the two-state model performs well for the behavioral data, we fitted the two-state model with three parameters: the variance ratio v/r, the variance ratio q/r, and the overall bias τ. The model outperformed the standard linear regression, reducing the Akaike Information Criterion (AIC) by 10.75, which indicates a markedly better fit to the behavioral data. Figure 3 shows the mean estimates for two Kalman gains, K_1 and K_2, along with the general bias (τ). On average, these Kalman gains K_1 and K_2 were lower in more predictable (low volatility) environments, while the general bias (τ) was elevated. Additionally, for the ASD group, K_2 was numerical higher and the bias (τ) numerically smaller when contrasted with the TD group.

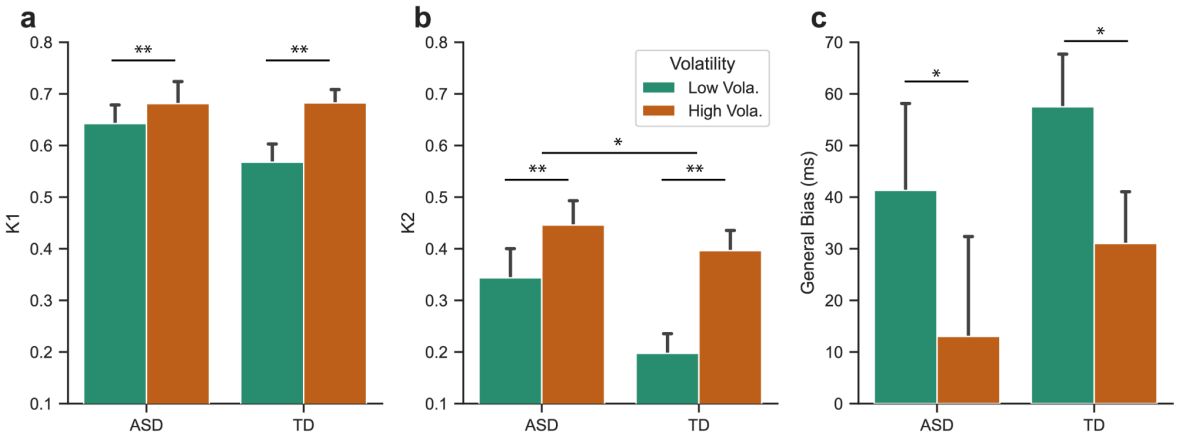

Figure 4. (**a**) The estimated Kalman gain K_1 for the state of duration prediction; (**b**) the estimated Kalman gain K_2 for the prior belief updating; (**c**) the general overestimation (ms), separated for two groups (ASD vs. TD) and the volatility sessions (Low vs. High). Each group n=32. Error bars denote one standard error. * denotes $p < .05$, ** $p < .01$.

A mixed ANOVA investigating the Kalman gain K_1, with Group and Volatility as factors, showed that only Volatility significantly impacts K_1, $F(1, 62) = 10.61$, $p = 0.002$, $\eta_p^2 = .146$. Specifically, the weight K_1 was higher during the high (68.2%) relative to the low (60.5%) volatility session, indicating that participants relied more on sensory input than their prior when making estimates in the high-volatile session. There was no main effect of Group or interaction of Group, Fs < 2.62, ps > .11, η_p^2s< .04.

Conversely, a similar analysis on the Kalman gain K_2 revealed a significant group difference, $F(1,62) = 4.23$, $p = 0.04$, $\eta_p^2 = .146$. On average, individuals with ASD exhibited a higher K_2 (0.395) than their counterparts (0.297), suggesting a greater tendency among individuals with ASD to revise their beliefs. Volatility also had a significant effect on K_2, $F(1,62) = 11.75$, $p = 0.001$, $\eta_p^2 = .159$, where participants were more inclined to update their internal beliefs in the high volatile (0.42) relative to low volatile (0.27) environments. The interaction between Group and Volatility, however, was non-significant, $F(1,62) = 1.21$, $p =$

0.276, η_p^2=.019. Additionally, another mixed ANOVA revealed that Volatility was the only significant factor affecting the general bias, $F(1, 62) = 11.83$, $p = 0.001$, η_p^2=.16, corroborating earlier reported behavioral results. Neither Group nor the interaction between Group and Volatility showed significant effects, Fs < 0.794, ps > .37, $\eta_p^2 s$< .013.

These tests revealed volatility impacted all three parameters examined, and a significant difference between the two groups was observed specifically in Kalman gain K_2.

Impact of updating parameters on the weight of the prior

To further investigate whether a greater emphasis on sensory input, indicated by a higher Kalman gain K_2, in short-term belief updating affects the speed of developing long-term prior beliefs, we analyzed the first half of each session's trials. We hypothesized that if individuals with ASD started with a low weight of prior and update these beliefs slowly, a reduced central tendency effect might be noticeable early in the session.

Given that we only included half of the trials, this analysis excluded three outliers and their counterparts for better data quality. Figure 5a shows the central tendency effect from these initial trials. A mixed ANOVA revealed significant differences for both Group ($F(1, 56) = 6.236$, $p = .015$, η_p^2=.1) and Volatility ($F(1, 56) = 24.74$, $p < .001$, η_p^2=.31), in contrast to the non-significant main effect of Group when tested across all trials and even when excluding the outliers. The central tendency was smaller for the ASD group than for the TD group in these initial trials but comparable with their performance across all trials, indicating slower adaptation in individuals with ASD. Similar to the analysis of all trials, the Durbin-Watson (DW) values were significantly higher for the ASD group compared to the TD group already in the first-half of trials, $F(1, 56) = 7.2$, $p = .01$, η_p^2=.114 (Figure 5b).

We reestimated Kalman gains K_1 and K_2 using only the first half of the session's trials and compared to the parameters obtained with the entire trials. Interestingly, K_2 remained relatively stable and showed nonsignificant change, with variations within 2.2% across all conditions and groups (Fs < 0.074, ps > 0.74). However, K_2 already displayed

significant differences between Group ($F(1, 56) = 4.51$, $p = .038$, $\eta_p^2 = .075$) and Volatility ($F(1, 56) = 11.18$, $p < .001$, $\eta_p^2 = .167$) in these initial trials.

Kalman gain K_1 showed a significant main effect of Volatility in these initial trials ($F(1, 56) = 21.89$, $p < .001$, $\eta_p^2 = .281$). On average, participants placed 71.7% of their weight on the sensory input in the high-volatile session but only 58.2% in the low-volatile session. Numerically, individuals with ASD placed higher weight on the sensory input (68%) than the TD counterparts (62%), but the difference did not reach a significant level, $F(1, 56) = 1.91$, $p = .172$, $\eta_p^2 = .03$. There was also no significant interaction between Group and Volatility ($F(1, 56) = 0.02$, $p = .89$, $\eta_p^2 < .001$). However, compared to the second half of trials, there were significant changes of K_1 in Volatility ($F(1, 56) = 6.18$, $p = .016$, $\eta_p^2 = .099$). Specifically, there was an increase of 2.6% in the high-volatile session and a decrease of 4.2% in the low-volatile session - a net difference of 6.8%. The change was similar between the two groups, $F(1, 56) = 0.75$, $p = .39$, $\eta_p^2 = .013$, suggesting both groups adjusted their weighting similarly.

Thus, the process of short-term belief updating remained relatively stable throughout the trials, with a significantly higher Kalman gain K_2 observed in the ASD relative to the TD group. This difference in K_2 influenced the rate at which long-term beliefs are formed, which in turn affects the central tendency effect. A significant difference in the central tendency effect between the two groups was evident in the first half of the trials, but this difference diminished when considering the entire session.

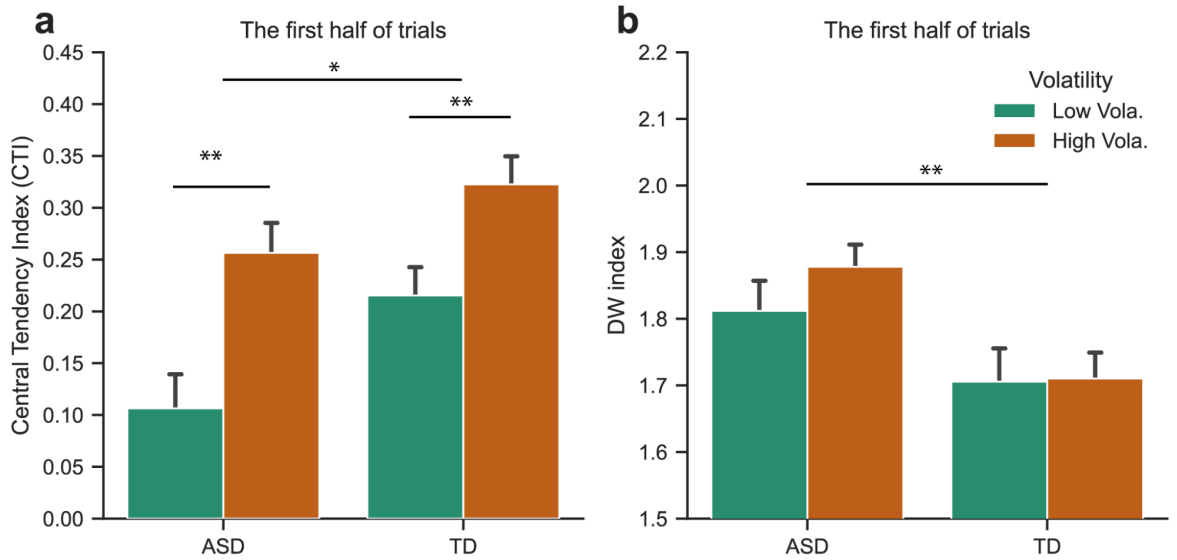

Figure 5. (**a**) The average central tendency indices (CTI) and associated standard errors for both the ASD and TD groups (each group n=29), differentiated according to high and low volatility sessions. A CTI of 0 implies a lack of a central tendency effect, whereas a CTI of 1 suggests a pronounced central tendency effect. (**b**) The average Durbin-Watson (DW) autocorrelation indices and associated errors, separated by the high and low volatility sessions, for both the ASD and TD groups. The dashed line, representing a DW value of 2.0, signifies the absence of autocorrelation, while a DW value less than 2 indicates a positive autocorrelation. Error bars denote one standard error. * denotes $p < .05$, ** $p < .01$.

Lastly, we further examined any potential relationships between estimated parameters and the symptom severity, measured by the Autism-Spectrum Quotient (AQ), Empathy Quotient (EQ), Systemizing Quotient (SQ), Beck's Depression Inventory (BDI), and Empathising-systemising (E-S) scores (see Appendix 2). We found a negative correlation between SQ and K_2 for both groups. Individuals with a higher SQ score had less updating weight K_2. However, individuals with ASD had significant higher K_2 than their counterparts.

Discussion

The underpinnings of differential predictive processing in ASD is a matter of current debate. In the present study we applied a two-state Bayesian model (Glasauer & Shi, 2022) that allows differentiating between two possible explanations for unique predictive

processing in individuals with ASD, namely: (a) weaker long-term prior beliefs (Karaminis et al., 2016; Pellicano & Burr, 2012), and (b) atypical short-term belief updating (Allenmark et al., 2021; Lieder et al., 2019; Vishne et al., 2021). The current findings indicate that predictive processing in ASD is characterized by distinct updating of short-term beliefs, as spelled out in the following.

Both groups responded to changes in volatility, showing a more pronounced central tendency effect in the high-volatility session compared to the low-volatility one in the duration reproduction task. Interestingly, in the first half of trials, the ASD group exhibited a smaller central tendency effect than the TD group, a group difference that disappears across the entirety of trials. Crucially, the two-state Bayesian iterative updating model revealed that individuals with ASD relied more on sensory input for updating their prior beliefs for the subsequent trial compared to TD counterparts, even though the influence of prior belief on duration estimation was similar across both groups.

Our results, showing distinctive iterative prior belief updating in individuals with ASD, align with the finding of a recent study employing suppression of salient distraction (Allenmark et al., 2021). Their study demonstrated that individuals with ASD effectively learned the probability of a salient distractor's location for suppression, yet they applied more suppression to locations where preceding trials held unexpected ('surprising') distractors, indicating a heightened update of their beliefs with surprise sensory inputs. It should be noted that in contrast to the attentional-capture salient distractors, the stimuli in the current study were consistent and yielded no surprise. Thus, the atypical updating of prior beliefs in our study depends much on the individual's perception of sequential continuity (Glasauer & Shi, 2022).

Importantly, this perspective may shed light on mixed findings previously reported about predictive processing in ASD. Past research has demonstrated that individuals with ASD are capable of forming appropriate priors through one-shot learning (Van de Cruys et al., 2018), from prior trials (Pell et al., 2016), or statistical settings (Hense et al., 2019; Pantelis & Kennedy, 2017). However, these studies often kept the volatility of the environment and the priors constant during and examined the final outcomes, possibly overlooking any atypical inter-trial updating. Our study suggests that the challenge for individuals with ASD lies not in the formation of prior beliefs, but in the ongoing, iterative process of updating these beliefs.

Similar to the current study, a paradigm varying volatility has been applied in previous research (Lawson et al., 2017). Indeed and in line with the previous study, our findings revealed that volatility played a significant role in forming the central tendency effect. However, both groups in the current study exhibited a stronger central tendency and a higher Kalman gain K_1 in the high- relative to the low-volatility session, suggesting their ability to adjust integration between prior beliefs and sensory inputs according to volatility of the respective environment. This adaptation differs from the previously suggested general overestimation of volatility in individuals with ASD (Lawson et al., 2017). Instead, it appears that individuals with ASD are more inclined to revise their interim prior beliefs with new sensory data. This suggests they perceive the world as having less temporal continuity and being more volatile. However, as we have shown, the effect is located at the level of belief updating, not their perception of the volatility of the sequence. Ultimately, both groups exhibited similar reliance on sensory input in their duration estimates across sessions with varying volatility.

The two-state Bayesian model (Glasauer & Shi, 2022) differentiates two types of updates: the revision of the current estimate (Eq. 4) and the modification of interim prior beliefs (Eq. 5). The fact that individuals with ASD placed more weight on sensory input when updating their interim beliefs implies they perceive temporal events as less interconnected than their TD counterparts, leading them to adjust their beliefs more based on sensory data. This process influences both their initial prior beliefs and the speed at which their prior beliefs are adapted to the environment. Consequently, in the first half of the session, they showed a weaker central tendency, yet by the session's end, they reached levels similar to their TD counterparts in both high and low-volatility environments. This aligns with the notion that individuals with ASD can accurately estimate environmental statistics, but their updating of internal priors is atypical compared to TD controls (Allenmark et al., 2021; Lieder et al., 2019; Vishne et al., 2021). Furthermore, an important refinement can be derived from the current results, showing that the

To some extent therefore, the atypicality of short-term belief updating found in the current study lends support to previous suggestions as being the main cause of its reduced adapting speed (Lieder et al., 2019; Vishne et al., 2021). For instance, in an examination of contraction bias (a type of central tendency bias) on tone discrimination task, Lieder et al.

(2019) found that individuals with ASD applied smaller weights to previous trials compared to controls, while their long-term weighting was similar. Importantly though, the atypical updating identified in our study differs. We found that it is not the direct integration of past information into estimations that varies between groups, but rather the updating of internal prior beliefs. To investigate whether the incorporation of recent history into estimates differed, we further conducted a general linear model (GLM) (detailed in Appendix 3) to include both current and previous durations to predict current reproduction errors. It revealed a significant difference in the weighting of the preceding duration between the high and low volatility, but not between groups, suggesting that the influence of preceding stimuli on duration judgments was similar across groups. It is important to note that this distinctive updating of prior beliefs in ASD should not be seen as a 'slower' process; rather, it is characterized by a heavier reliance on sensory inputs. In uncertain environments, this more 'volatile' updating in fact is advantageous, as it leads to a focus on sensory inputs over prior beliefs in duration estimation, resulting in a less pronounced central tendency effect during the first half of the sessions. However, this approach does lead to somewhat slow adaptation across the entire session.

The distinctive updating of prior beliefs might also shed light on conflicting findings in previous research on time perception, as the outcomes hinge on the rate of adaptation. As a result, some previous studies have found that individuals with ASD maintain an intact sensitivity to visual interval timing (Isaksson et al., 2018; Jones et al., 2009; Mostofsky et al., 2000; Poole et al., 2022), while others observed reduced sensitivity in ASD, especially with certain temporal intervals or auditory tasks (Falter, Noreika, et al., 2012; Isaksson et al., 2018; Martin et al., 2010; Szelag et al., 2004). Notably, a study by Karaminis (2016) examining duration reproduction in children with ASD revealed these children displayed a stronger central tendency and poorer temporal resolution when compared to their TD counterparts. Their Bayesian modeling indicated that the central tendency in children with ASD was weaker than theoretical models based on their performance would predict, indicating poorer priors compared to the control group. It is important to point out that Karaminis et al. (2016) used only 77 trials per session for children, fewer than the half-session trials (125 trials) in our current study. Therefore, the findings they reported may reflect the initial prior beliefs for trusting more on sensory inputs rather than poor priors in the children with ASD, which would be consistent with our analysis of the first half-session.

As a hypothesis derived from our current findings, extended testing might allow these children to develop similar prior beliefs as their TD counterparts.

It is worth noting that within the ASD group, three individuals out of our sample of 32 participants showed a marked deviation from the others, while also exhibiting strikingly similar response characteristics among themselves (see Appendix 1). For the relatively stable and predictable (i.e., the low-volatility) sequence, these individuals produced time intervals proportional to the target durations, albeit with some general over- or underestimation. However, for the volatile random sequences, they consistently reproduced the same duration across all sampled intervals. That is, in the high-volatility condition, they disregarded the external sensory inputs completely (K_1 and K_2 were 0.07 and 0.04 respectively) and relied solely on an overly strong internal prior duration. The normal reproduction performance in the low-volatile sequence effectively rules out that their deviant behavior is simply attributable to a misunderstanding of the instruction. Importantly, the participants reported no awareness of the difference in the randomization (i.e., sequential duration volatility) regimens between the two sessions during debriefing, suggesting that their performance was influenced implicitly. One speculative explanation for this extreme behavior is that these participants may have responded by 'shutting out' the sensory input when confronted with a highly volatile sequence. It should be noted that even when including these outliers in our analysis, the results remained similar for the two-state model.

In conclusion, our findings clarify inconsistencies and refine findings from previous research into predictive processing in ASD. We found that while individuals with ASD use prior knowledge in a manner similar to controls, they place greater emphasis on sensory information specifically to updating interim beliefs. This distinctive process may lead to slow adaptation across trials, which, depending on the environmental volatility, is not necessarily a disadvantage. The varied findings in existing literature might stem from examining different stages of adaptation. Our observations indicate that individuals with ASD can adapt to various environments (such as those with high or low volatility), but the process of updating beliefs is distinct. Our study, along with the two-state iterative updating model, highlights the unique short-term, inter-trial dynamics in individuals with ASD. It proposes a hypothesis that emphasizes temporal discontinuity and overreliance on sensory input specifically in the moment-to-moment belief updating as a key signature of ASD.

Methods

(a) Participants

32 individuals (13 females, 19 males, aged between 18 and 67 years, $M = 32.0$; $SD = 12.3$) with confirmed ICD-10 ASD diagnosis (World Health Organization, 1992) of F84.0 or F84.5 were recruited from the database and network partners of the Outpatient Clinic for Autism Spectrum Disorders at the Department of Psychiatry, LMU Munich, Munich, Germany. 32 TD controls (13 females, 19 males, aged between 18 and 70 years, $M = 31.6$, $SD = 13.6$) with no reported history of mental illnesses or neurological deficits were recruited via local advertising. The groups were matched pairwise using the 'Wortschatztest' (WST) (Schmidt & Metzler, 1992), a measure of crystalline intelligence. Both groups completed the Autism-Spectrum Quotient (AQ) (Baron-Cohen et al., 2001), Empathy Quotient (EQ) (Baron-Cohen & Wheelwright, 2004), Systemizing Quotient (SQ) (Baron-Cohen et al., 2003), and Beck's Depression Inventory (BDI) (Beck et al., 2011) as proxies of symptom load. The groups did not differ significantly in terms of IQ (p=.28), age (p=.9), but differed significantly on AQ ($p < .001$), EQ ($p < .001$), SQ ($p = .005$), and BDI (p=.018). In addition, we calculated the empathising-systemising (E-S) score by the difference between EQ and SQ, which also showed a significant difference ($p < .001$) (see Appendix 3, Table A2).

All participants provided written informed consent prior to the experiment and received compensation of 10 Euro per hour for their service. The study was approved by the Ethics Board of the Faculty of Pedagogics and Psychology at LMU Munich, Munich, Germany.

(b) Design and procedure

The experiment took place in an experimental cabin with attenuated sound and moderate lighting conditions. A visual stimulus in the form of a yellow disk patch (with a diameter of 4.7° of visual angle and luminance of 21.7 cd/m^2) was used for delivering durations on a 21-inch LACIE CRT monitor with a refresh rate of 85 Hz. The experimental code was developed using the Matlab PsychToolbox (Kleiner et al., 2007).

We adopted the duration reproduction paradigm (Ren et al., 2021) (Figure 1a). A trial started with a central fixation cross (with a size of 0.75°) for 500 ms, followed by a white dot (with a diameter of 0.2°), signaling participants to press and hold the mouse button (either left or right) to initiate the encoding phase. Once the mouse button was pressed, a yellow circle appeared on the screen for a randomly chosen duration ranging from 100 ms to 1900 ms (elaborated in the next paragraph). The yellow disk then disappeared, prompting the participant to immediately release the key. A blank screen lasting 500 ms separated the encoding and reproduction phases. Next, a white dot appeared, indicating to participants that they needed to reproduce the duration they had just observed. They were instructed to press and hold the mouse button for a duration matching the previously displayed yellow circle, then release it. On pressing the mouse button, a yellow disk reappeared on the central display and disappeared once the button was released. Subsequently, a feedback display appeared for 500 ms, providing information on the accuracy of the reproduction. The feedback was based on the ratio of the reproduction error relative to the actual duration. The feedback display included five horizontally arranged disks, with the relative error ranges mapped as follows, from left to right: less than -30%; between -30% and -5%, between -5% and 5%, between 5% and 30%, and greater than 30%. The three central circles were highlighted in green, whereas the left and right outer discs were highlighted in red, indicating a large error that should be avoided.

The experiment consisted of two sessions, both including the same set of stimulus durations and an equal number of duration repetitions, but the sessions differed in terms of the presentation order. Each session comprised 10 blocks, each containing 25 trials. The sequence of durations was generated using a random-walk process, which began with a randomly selected duration, and the duration of each trial was determined by the duration of the previous trial with a small random fluctuation introduced. Over the course of 250 trials, these fluctuations occasionally accumulated and might exceed the desired range (e.g., negative values). To address this, we scaled the durations back to fit within 100 ms to 1900 ms, and rounded them to the nearest 100-ms value, allowing for multiple repetitions of the tested durations. This approach yielded a sequence with mild fluctuations across trials, termed the “low volatile” sequence. Next, we randomly shuffled the durations from this sequence to create a new sequence, termed the “high volatile” sequence, with greater trial-to-trial variations, compared to the “low volatile” sequence. Figure 1b illustrates typical

sequences for the low- and high-volatility sequences across two consecutive sessions. Both sequences were generated prior to the experiment, and the order of the low- and high-volatility sessions was counterbalanced across participants.

It is important to note that we administered identical sequences to (age- and IQ-) matched participants in both the ASD and TD groups, ensuring that any differences observed truly reflected distinctions between the two groups. Prior to the experiment, participants received comprehensive written and verbal instructions, and they underwent a pre-experimental training session of at least 10 trials to ensure their understanding of the instructions. Subsequently, the experiment proper was conducted followed by filling out the questionnaires.

Ethic. The study was approved by the Ethics Board of the Faculty of Pedagogics and Psychology at LMU Munich, Germany (29.05.2018).

Data accessibility

Experimental codes, data, and analyses are published at g-node: 10.12751/g-node.85py1h.

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Appendix

Appendix 1. Outlier reproductions in the high-volatility session from the ASD group

In the high-volatility session from the ASD group, three individuals exhibited marked different performance trends compared to the rest of the group (see Figure 3 Boxplots). To better visualize their reproduction performance, we replot their reproduced durations as a function of the duration. Figure S1 illustrates their performance for the low and high volatility sessions. The reproduced durations were similar across the range of durations in the high-volatility session (orange, 'flat'), even though their performance in the low-volatility session aligned with their peers. For these three outliers, the central tendency indices (1 - regression coefficient) during the high volatility session were extremely high (0.904, 0.997, and 0.907), suggesting they heavily relied on their prior instead of sensory duration inputs, exhibiting a remarkable level of rigidity in their responses.

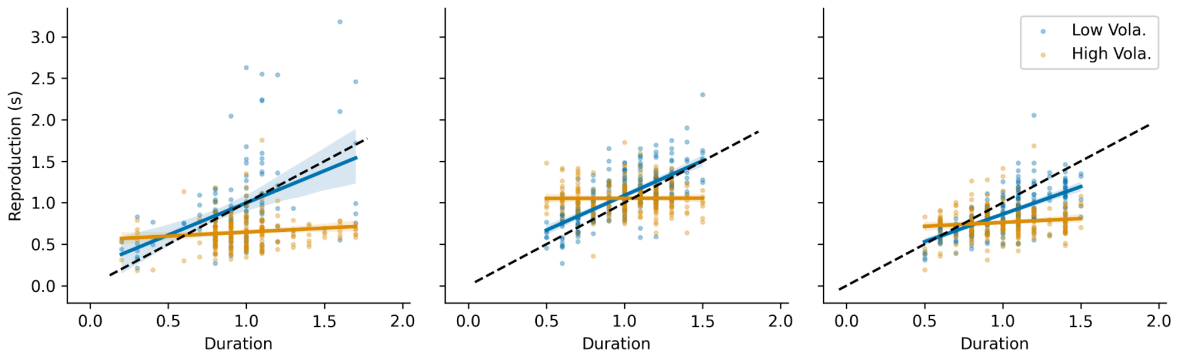

Figure S1. Duration reproduction by three 'extreme' ASD individuals, separated for the high- (orange) and low-volatility (blue) sessions. The diagonal dashed line denotes veridical reproduction.

Appendix 2. Correlations between updating weight and symptom severity

We examined any potential relationships between estimated parameters and the symptom severity, measured by the Autism-Spectrum Quotient (AQ), Empathy Quotient

(EQ), Systemizing Quotient (SQ), Beck's Depression Inventory (BDI), and Empathising-systemising (E-S) scores. In addition, we considered potential contributions offrom the main factors of Group and Volatility. We found a strong negative correlation between K_2 and SQ (p = .003), and a strong positive correlation between K_2 and E-S (p = .016) scores. The estimated linear models were:

$$K_2 = 0.660 - 0.155G_{TD} - 0.158V_{low} - 0.005 \cdot SQ, \quad (6)$$

$$K_2 = 0.496 - 0.195G_{TD} - 0.158V_{low} + 0.003 \cdot ES, \quad (7)$$

where G_{TD} was a dummy variable for the TD group, V_{low} for the low volatility session. Intercepts and coefficients for the dummy variables were all significant (p < .001). The K_2 was significantly higher for the ASD group compared to the TD group (15.5% and 19.5% in the above two estimated models). Figure S2 shows the correlation trends for both scores. Given that E-S scores were derived from the difference between Systemizing Quotient (SQ) and Empathy Quotient (EQ), SQ is likely the main driven factor for the correlation.

The correlation suggests the updating weight K_2 is sensitive to individual preference and aptitude for systemizing. The higher systemizing preference, the smaller the updating weight of sensory data to their prior beliefs.

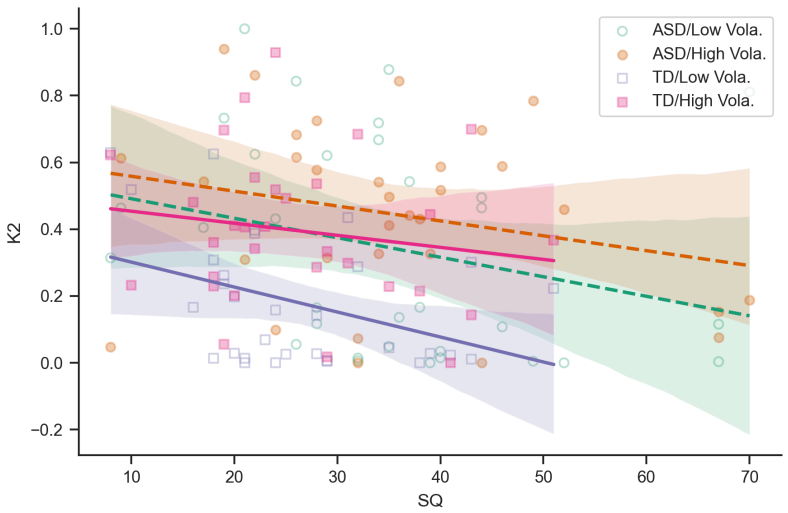

Figure S2. Negative correlations between K_2 and Systemizing Quotient (SQ) scores separated for the ASD and TD groups, and the high and low volatile sessions.

Appendix 3. A general linear model (GLM) considering preceding trial

To determine if there were any differences in how the two groups incorporated short-term trial history, we conducted a general linear model (GLM) that factored in both current and previous durations to predict current reproduction errors. Considering that in the low volatility session the current and previous durations were not fully independent, we used the difference ($\Delta D = D_n - D_{n-1}$) from the previous trial in our regression model. Additionally, to mitigate the impact of extreme outliers, we removed the three outliers and their matched pair from the analysis. Table A1 displays the average regression coefficients and their associated standard errors.

We then performed separate mixed ANOVAs for each coefficient, considering the factors of Group and Volatility. The analysis failed to reveal any significant group and volatility differences in the intercept. The coefficients for the Current Duration D_n varied significantly between high and low volatility sessions, $F(1,56) = 24.57$, $p < .001$, $\eta_p^2 = .305$. However, the main factor Group and the interaction between Group and Volatility failed to reach significance, Fs < 2.218, ps > .14, $\eta_p^2 s < .038$. Similarly, the coefficients for the deviation ΔD differed significantly for high and low volatility sessions, $F(1,56) = 54.49$, $p < .001$, $\eta_p^2 = .489$, but not for Group or the interaction between group and Volatility, Fs < 3.34, ps > .073, $\eta_p^2 s < .056$. This analysis indicates that the impact of the previous Duration was similar for both groups.

Table A1. the average regression coefficients and their associated standard errors (in brackets) for ASD and TD group, separated for the high and low volatility sessions.

Group	Volatility	Intercept	Current Duration (D_n)	$D_n - D_{n-1}$
ASD	High	0.032 (0.015)	-0.166 (0.026)	-0.104 (0.016)
	Low	0.042 (0.015)	-0.092 (0.030)	-0.281 (0.041)
TD	High	0.029 (0.011)	-0.224 (0.023)	-0.123 (0.012)
	Low	0.038 (0.013)	-0.086 (0.021)	-0.394 (0.049)

Appendix 3: Descriptive characteristics of the ASD and TD groups

The groups were matched pairwise using the 'Wortschatztest'(WST, Schmidt & Metzler, 1992), a measure of crystalline intelligence. Both groups completed the Autism-Spectrum

Quotient(AQ, Baron-Cohen et al., 2001), Empathy Quotient(EQ, Baron-Cohen & Wheelwright, 2004), Systemizing Quotient(SQ, Baron-Cohen et al., 2003), and Beck's Depression Inventory(BDI, Beck et al., 2011). The mean scores and paired *t*-tests are shown in Table A2. As can be seen, AQ, EQ, SQ, and BDI scores were significantly different between two groups.

Table A2. *Descriptive characteristics (Means and SDs) for ASD and TD group.*

Measures	***ASD (n=32)***	***TD (n=32)***	***Group comparison***
Age	32.03 (12.3)	31.6 (13.6)	$t_{31} = 0.13, p = .898$
IQ score	107.4 (9.7)	109.1 (13.4)	$t_{31} = 0.573, p = .28$
Autism-Spectrum Quotient score	36.7 (7.4)	15.8 (6.0)	$t_{31} = 18.06, p < .001^{**}$
Empathy Quotient score	26.97 (12.32)	50.38 (14.46)	$t_{31} = -7.85, p < .001^{**}$
Systemizing Quotient score	35.25 (14.93)	26.63 (10.1)	$t_{31} = 3.05, p < .01^{**}$
Beck's Depression Inventory score	10.69 (8.37)	5.25 (7.46)	$t_{31} = 2.49, p = .018^{*}$

Note: ** denotes p < .05 and ** p < .001.