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ORIGINAL ARTICLE

# Predictive Processing During Cue-Outcome Associative Learning in Autistic Children

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## Abstract

**Purpose** Predictive coding theories posit that autism is characterized by an over-adjustment to prediction errors, resulting in frequent updates of prior beliefs. Atypical weighting of prediction errors is generally considered to negatively impact the construction of stable models of the world, but may also yield beneficial effects. In a novel associative learning paradigm, we investigated whether unexpected events trigger faster learning updates in favour of subtle but fully predictive cues in autistic children compared to their non-autistic counterparts. We also explored the relationship between children's language proficiency and their predictive performances.

**Methods** Anticipatory fixations and explicit predictions were recorded during three associative learning tasks with deterministic or probabilistic contingencies. One of the probabilistic tasks was designed so that a fully predictive but subtle cue was overshadowed by a less predictive salient one.

**Results** Both autistic and non-autistic children based their learning on the salient cue, and, contrary to our predictions, showed no signs of updating in favour of the subtle cue. While both groups demonstrated associative learning, autistic children made less accurate explicit predictions than their non-autistic peers in all tasks. Explicit prediction performances were positively correlated with language proficiency in non-autistic children, but no such correlation was observed in autistic children.

**Conclusion** These results suggest no over-adjustment to prediction errors in autistic children and highlight the need to control for general performance in cue-outcome associative learning in predictive processing studies. Further research is needed to explore the nature of the relationship between predictive processing and language development in autism.

**Keywords** Autism · Predictive processing · Associative learning · Eye-tracking · Language

## Introduction

Predictive processing theories conceptualize perception as an active process that arises from the interplay between sensory input and predictions about the environment (Friston, 2010; Rao & Ballard, 1999). Human brain consistently relies on prior knowledge to anticipate future events. However, in changing environments, discrepancies between predictions and sensory inputs can emerge, giving rise to what is commonly referred to as *prediction errors*. Prediction errors thus play a central role in predictive processing, as they can signal a relevant change in the environment. However, prediction errors can also arise from environmental noise. An effective adaptive strategy is then to distinguish relevant prediction errors–the ones that signal that prior beliefs need to be updated to optimize future predictions–from irrelevant prediction errors, after which any priors' update could be unfruitful. A mechanism called *precision weighting* can be used to model the significance of each prediction error (Friston, 2009, 2010). In a stable environment, precision weighting tends to be low, leading to prediction errors being ignored. Conversely, in an uncertain and volatile environment, precision weighting tends to be high, amplifying the impact of prediction errors (Behrens et al., 2007). In the latter case, increased sensory load and active inference, such

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as attentional exploration, can help reduce uncertainty by enabling the search for new information, which can then be used to update one's beliefs (Friston et al., 2012, 2016).

Several authors proposed that main features of autism—such as sensory overload, perceptual atypicalities, and motor or social difficulties—stem from an imbalance in precision weighting (Chrysaitis & Seriès, 2023; Van de Cruys et al., 2014; for a review see Cannon et al., 2021). One view is that precision weighting is atypically high and inflexible in autistic individuals (Van de Cruys et al., 2014), while another is that autistic individuals overestimate the volatility of their environment, leading to poor adaptation of precision weighting (Lawson et al., 2017). On both views, autistic individuals would allocate excessive weight to their prediction errors, resulting in an elevated sensory load and to a high rate of prior updates in situations where non-autistic individuals would have maintained their priors unchanged. Excessive prior updating may lead autistic individuals to perceive the environment as unpredictable and chaotic. Repetitive behaviours and narrow interests, which are among the core characteristics of autism, may therefore emerge as coping mechanisms to impose structure on an unstable world (Van de Cruys et al., 2014).

The models that posit atypical predictive processing in autistic adults are supported by various types of experimental evidence: higher surprise reactions to unexpected events (van Laarhoven et al., 2020), poor adaptation of precision weighing to changes in the environment (Goris et al., 2018; Lawson et al., 2017; Sapey Triomphe et al., 2021; Thillay et al., 2016), and higher learning rates and faster learning updates in uncertain situations (Allenmark et al., 2021; Crawley et al., 2020; Goris et al., 2022). At the same time, several such studies found no group differences (Manning et al., 2017; Van de Cruys et al., 2021; Ward et al., 2021).

Early theories of atypical predictive coding in autism pointed to a potential connection with strengths sometimes observed in this population, such as enhanced perceptual abilities or systemizing skills (Van de Cruys et al., 2014). Yet, an atypically high rate of learning updates has mostly been described as negatively impacting the construction of relevant and stable priors (Crawley et al., 2020; Lawson et al., 2017). However, the detrimental role of over-adjustment to prediction errors could be task-dependent and mostly apparent in situations where only one cue is predictive of each outcome with a probability superior to 0.5. For instance, in a learning phase that involves two cues (A and B) and two outcomes (X and Y), where cue A is predictive of outcome X 80% of the time (ProbA➔X = 0.8) and predictive of outcome Y 20% of the time (ProbA➔Y = 0.2), while ProbB➔Y = 0.8 and ProbB➔X = 0.2, then A➔Y and B➔X would be treated as oddball events and induce prediction errors. Therefore, any learning update attempts after these errors would be unfruitful and detrimental for A➔X and B➔Y associative strengths since the only other available associations (A➔Y and B➔X) are only 20% predictive.

Therefore, the potential benefits of a higher rate of prior update on learning in autistic individuals could be observed using paradigms with more complex mappings than the classically used straightforward one-to-one cue-outcome associations. One way of exploring that possibility could be investigating the consequences of mismatches between the predictiveness of cues and their physical salience. If a physically salient cue overshadows a subtler but more predictive cue, autistic participants should update their learning based on the subtler cue more rapidly than non-autistic individuals after experiencing the unexpected outcome of the salient cue. The hypothetical positive effect of precision imbalance on the learning of subtle, yet more predictive associations aligns with the observation of enhanced abilities to detect repetitive patterns and highly regular structures in autistic individuals and adults with elevated autistic traits (Baron-Cohen et al., 2003; Goris et al., 2020; Mottron et al., 2013). Using different learning paradigms may, therefore, highlight alternative rather than impaired learning outcomes and contribute to a deeper understanding of autism symptomatology.

Atypical language development is a core characteristic of autism that stands to gain significant insights from the examination of precision imbalance (Weismer & Saffran, 2022). Language delays affect up to 50% of children on the autism spectrum, with 20–30% never achieving functional language (Wodka et al., 2013). Linguistic disabilities observed in autism include delays in early vocabulary development (Luyster et al., 2008; Weismer & Kover, 2015), atypical word mapping learning (Hartley et al., 2014), over-specified learning of lexical category (Church et al., 2010; Gastgeb & Strauss, 2012; Soulières et al., 2007) as well as grammatical and pragmatic impairments (Eigsti et al., 2011; Wittke et al., 2017).

Arguably, the categorisation and generalisation of lexical information requires a selective rejection of prediction errors. Assigning too much weight to non-significant difference between events in the same category could lead to an overfitting of lexical or categorical learning, preventing the creation of higher-order representations. Moreover, if atypical predictive coding leads to a different way of prioritizing cues —such as the preference for subtle yet fully predictive cues in autistic individuals and salient but less predictive cues in non-autistic individuals—it could have a differential impact on word mapping and lexical acquisition in general. In the same vein, atypical attentional selectivity favouring local cues over global information has been shown to correlate with poor interaction and communication skills in autistic individuals (Klin et al., 2002; Yoon et al., 2024).

Some studies provide neural evidence of the link between prediction errors and typical language comprehension (Ryskin & Nieuwland, 2023; Wang et al., 2023). Other studies have focused on the relationship between predictive processing and typical language abilities, linking receptive vocabulary and mismatch response amplitudes in 12-month-olds (Ylinen et al., 2017), or between vocabulary size and predictive gaze abilities in children and adults (Borovsky et al., 2012; Mani & Huettig, 2012). In a similar vein, Reuter and colleagues (2019) observed that prediction errors positively influenced word learning in 3- to 5-year-olds, while Reuter et al. (2018) reported a relation between learning updates in nonverbal tasks and vocabulary level at this age. Studies have also shown that atypical predictive processing can affect the learning of grammatical rules and the development of syntactic awareness in populations with developmental language disorders (Hestvik et al., 2022; Jones & Westermann, 2021).

The few studies to have explored the interaction between predictive processing and language in autism have focused on incremental language processing, using object-focused attention as an indicator of sentence anticipation. These studies have demonstrated accurate predictions (Bavin et al., 2016; Zhou et al., 2019) and a positive relationship between predictions and general language abilities in both autistic and non-autistic groups (Prescott et al., 2022; Venker et al., 2019). While the predictive framework seems promising for understanding atypical language development in autism (Weismer & Saffran, 2022), no study, to our knowledge, has explored the link between predictive update processing and language in autistic individuals.

This study focused on children aged between 9 and 16, a population expected to show variability in language skills while being able to comprehend the instructions and maintain their attention throughout the tasks. We employed a novel associative learning paradigm that introduced competition between a physically salient cue and a subtler but more predictive one. We hypothesized that if a salient cue, which was 80% predictive of an outcome, overshadowed a subtler cue that was 100% predictive of the same outcome, autistic participants would demonstrate greater attentional exploration after having experienced unexpected salient associations. We also expected autistic participants to update their learning based on the subtler cue more rapidly than non-autistic individuals. Additionally, we hypothesized positive associations between participants' general language abilities, vocabulary levels, and overall predictive accuracy. Conversely, we predicted a negative correlation between the number of unfruitful update attempts and participants' language indexes.

We recorded participants' explicit predictions as well as their anticipatory fixations. This bi-variable design aimed to address recent findings suggesting that atypical prediction processing in autism may be more prominent in low-level predictive processing, such as predictive eye movements, or in tasks where the association of cues with outcomes is not explicitly stated (Cannon et al., 2021; Amoruso et al., 2019). Moreover, given the challenges associated with testing autistic children and widespread data loss, particularly when applying a new experimental paradigm, combining explicit and implicit responses should maximize the data reliability.

## Methods

### Participants

The sample was composed of twenty-three autistic children (9 female; age range 9–16 years, M = 11, SD = 2.06), and twenty-three non-autistic children (11 female; age range 9–12 years, M = 10.5; SD = 1.08). Total Intelligence Quotient scores significantly differ between autistic participants (M = 96.7, SD = 17.9) and non-autistic participants (M = 112, SD = 8.77). The influence of participants' IQ scores on our main dependent variables was controlled for throughout our analyses. Participants' detailed demographic information is available in Appendix 1.

### Participants' Recruitment

Participants were recruited through various channels, including our lab's database, distribution of flyers, social media outreach, and direct engagement with primary schools (for the non-autistic group) and special education schools (for the autistic group). Inclusion criteria for the non-autistic group were: French as at least one primary language and the absence of known neurodevelopmental or psychiatric conditions. For autistic participants, inclusion criteria were French as at least one primary language and an official diagnosis of Autism Spectrum Disorder from a multidisciplinary team. All participants had either normal vision or corrected-to-normal vision and normal hearing. All participants received a 10 euros bookshop voucher as compensation for taking part in the study. Written consent was obtained from all participants and their parents. This study was approved by Erasme-ULB Hospital-Faculty Ethics Committee (register number CCB: B4062022000135).

## Materials

### Task

We presented participants with two visual stimuli, characterized by their overall shape and a subtle filling pattern. In each trial, we played one of two distinct sounds after one of the visual stimuli became animated. Participants were explicitly asked to predict which stimuli would animate using the keyboard, and their gazes were recorded between the onset of the sound and their response. The experiment consisted of three blocks detailed in Table 1 (for more information, refer to the Block Design section in Appendix 1). In the Deterministic block, each sound was fully predictive of the animation of one of the two stimuli. In the Probabilistic block, each sound was predictive of the animation of one of the two stimuli with a contingency of 80:20. The Dual block also contained 20% of oddball trials, but unlike in the Probabilistic block, the patterns between the two shapes were swapped during the oddball trials. Therefore, in the Dual block, the sound-shape association also predicted the animation of one of the two stimuli in an 80:20 ratio. However, the sound-pattern association predicted the animation of one of the two stimuli with a probability of 100:0.

## Stimuli

Within each block, two asemantic 400 ms sounds (A1 and A2), which were easily distinguishable from each other, signalled the upcoming animation of one of two visual stimuli. Visual animations were thus used both as outcomes, and as reinforcement inducing participants to make anticipatory fixations on the about-to-move stimulus (details about the nature of the animations are provided in Appendix 1). As illustrated in Fig. 1, the two visual stimuli consisted of two non-semantic shapes (S1 and S2), each filled with a pattern oriented either upwards (P1) or downwards (P2). The same shapes and stimuli were used in the Deterministic and the Dual blocks, while the Probabilistic block featured two different shapes and two different filling patterns. From now on, the auditory and visual stimuli from the Probabilistic block will be indexed with the $^{Prob}$ super-script (details on stimuli in Appendix 1). Following Byrom and Murphy (2019), we considered the shapes of our visual stimuli (S1 and S2) as the salient dimension and the filling patterns of these stimuli (P1 and P2) as the subtle physical dimension. Shapes and filling patterns could then be associated in four different ways: S1P1, S1P2, S2P1 and S2P2. As shown in Fig. 1, the two visual stimuli presented simultaneously on the left and right halves of the screen could be either [S1P1 and S2P2] or [S1P2 and S2P1], depending on the block. All visual stimuli measured 380 by 525 pixels, each covering 10% of the 1920 × 1080-pixel screen (refer to Appendix 1 for technical equipment information).

## Design

### Intra-trial Design

Participants' learning was assessed through their explicit predictions about the outcome and their anticipatory gazes. Each trial consisted in four different phases, illustrated in Fig. 2. During the first phase, the two visual stimuli were presented simultaneously, one on each side of the screen, with the sides counterbalanced across trials. After 1400 ms, one of the two sounds was played for 400 ms. Next, the anticipation phase began, during which both visual stimuli remained visible on the screen. During this anticipation phase, participants were required to predict which stimulus would move by pressing the left or right arrow on their keyboard. When a key was pressed, the sound-associated stimulus animated for 1920 ms; otherwise, animation initiated after 6 s. After that animation phase, the two visual stimuli disappeared, and the next trial started. Each block consisted of 32 trials and lasting about 3 min on average. Participants' gazes were recorded during each of the 32 testing trials,

**Table 1** Block designs. A1 and A2 are auditory cues, S1 and S2 are shapes and P1 and P2 are filling patterns. The animation or absence of animation of each visual stimulus (the outcome) is respectively represented by a (+) or a (-)

| | Associations | Trials | Sound | Visual stimulus | | |
|---|---|---|---|---|---|---|
| Deterministic block | Deterministic association | standard | A1 | S1P1 + | & | S2P2 – |
| | | 32 / 32 | A2 | S1P1 – | & | S2P2 + |
| | | oddball | | / | | |
| | | 0 / 32 | | | | |
| Dual block | Dual association | standard | A1 | S1P1 + | & | S2P2 – |
| | predictiveness: | 26 / 32 | A2 | S1P1 – | & | S2P2 + |
| | sound-pattern 100% | oddball | A1 | S1P2 – | & | S2P1 + |
| | sound-shape 80% | 6 / 32 | A2 | S1P2 + | & | S2P1 – |
| Probabilistic block | Probabilistic association | standard | $A1^{Prob}$ | $S1^{Prob}$ $P1^{Prob}$ + | && | $S2^{Prob}$ $P2^{Prob}$ – |
| | | 26 / 32 | $A2^{Prob}$ | $S1^{Prob}$ $P1^{Prob}$ – | | $S2^{Prob}$ $P2^{Prob}$ + |
| | | oddball | $A1^{Prob}$ | $S1^{Prob}$ $P1^{Prob}$ – | & | $S2^{Prob}$ $P2^{Prob}$ + |
| | | 6 / 32 | $A2^{Prob}$ | $S1^{Prob}$ $P1^{Prob}$ + | & | $S2^{Prob}$ $P2^{Prob}$ – |

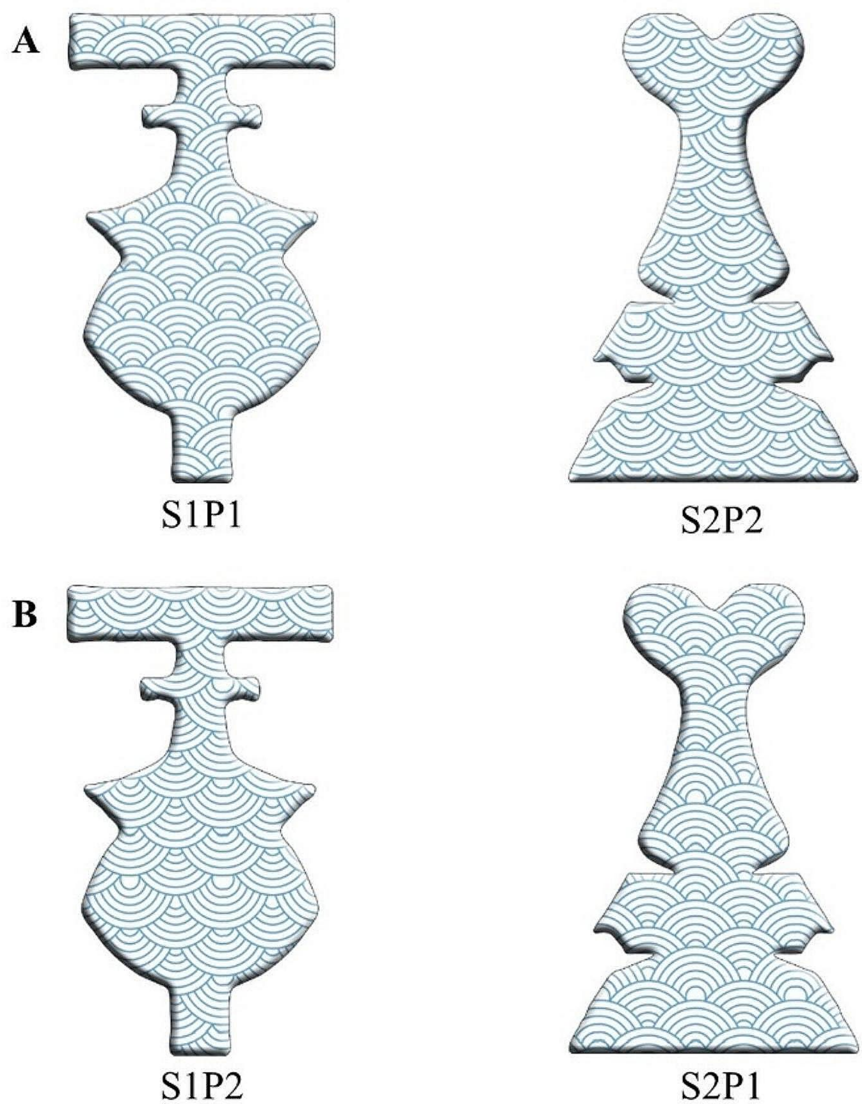


**Fig. 1** Visual stimuli used in the Deterministic and Dual block. Each stimulus has one of two shapes (S1 and S2) and is filled with one of two patterns (P1 and P2). The two stimuli shown in **A** were used in all trials of the Deterministic block and in the standard trials of the Dual block. The two stimuli shown in **B** were used during the oddball trials of the Dual block

beginning with the onset of the sound and extending until a key press occurred. If no key was pressed, the eye recording continued until the next trial.

#### Psychometric Measures

Participants' Intellectual Quotient (IQ) was assessed using the full version of the Wechsler Intelligence Scale for Children (WISC-V; Wechsler, 2014). The WISC-V is used to assess the cognitive abilities of children aged 6 to 16 and consists of 10 primary subtests that contribute to five main composite scores: Verbal Comprehension Index, Visual Spatial Index, Fluid Reasoning Index, Working Memory Index, and Processing Speed Index. These composite scores can provide an overall assessment of a child's cognitive abilities. The WISC-V Vocabulary subset, which accounts in part for the Verbal Comprehension Index, was used to assess participants' lexical proficiency.

We used the core language index of the Clinical Evaluation of Language Fundamentals - Fifth Edition (CELF-5, Wiig et al., 2013) to measure participants general language skills. CELF-5 features a range of subtests and composite scores assessing language skills in individuals aged 5 to 18. Subtests cover receptive and expressive language domains, including comprehension, vocabulary, and sentence structure. The composite Core Language Score, provide an overall profile of language abilities, with higher scores indicating better language proficiency.

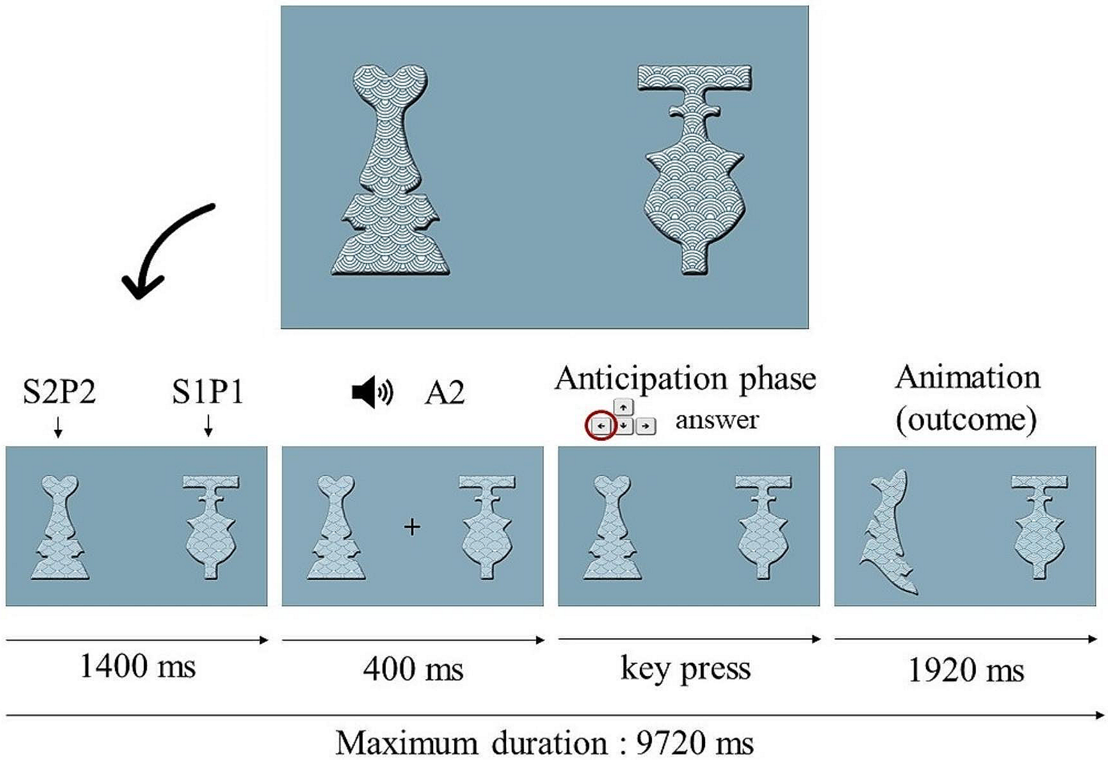


**Fig. 2** Example of a trial from the Deterministic block

### Questionnaires

Parents were asked to complete the Children's Communication Checklist (CCC-2) (Bishop, 2003), which is a comprehensive tool designed to assess pragmatic and communication skills in individuals aged 4 to 16 years. This checklist evaluates various domains of communication, including speech, semantics, and social aspects such as initiating and maintaining conversations, understanding non-literal language, and using appropriate gestures. We used the General Communication Composite score (GCC), which is employed to identify children with a high likelihood of having clinically significant communication difficulty. Higher GCC scores indicate better communicative skills.

Finally, parents completed our laboratory questionnaire, adapted from the revised Family Affluence Scale (Currie et al., 2008) which serves as a proxy for the participant's socio-economic background. It includes an education score on a 0- to 6-point scale, ranging from 0 (indicating no primary school achievement) to 6 (representing a doctoral degree), and an economic status on a 0- to 13-point scale, where 0 corresponds to very low economic status, and 13 reflects very high economic status. The addition of these two scores is used and an index of families' Socio-Economic Status (SES).

### Sessions

The experiment was conducted across two sessions, with a minimum gap of one day and a maximum of one week between them. At the onset of the initial session, we provided parents with questionnaires and consent forms. Then we set up the computer and eye-tracking equipment while familiarizing with the participant. The participant then completed the Probabilistic block, followed by the Visual Puzzle and Picture Span subtests of the WISC-V. Afterwards, they had a 15-minute break, during which they were free to choose any activity except screen-related ones, and after which they completed the Deterministic block, immediately followed by the Dual block. The remaining WISC subtests were then administered, and we collected the questionnaires. The brief interval between the Probabilistic and Deterministic blocks aimed to prevent fatigue and disengagement in autistic participants, as well as to avoid undesired direct learning generalization between the Probabilistic and the two other blocks. The assessment of the CELF-5 took place during the second session before participants completed two other learning tasks not related to that study.

The sessions were conducted in an experimental room with lighting optimized for eye-tracking studies. All details regarding eye-tracking data processing, data preparation, instructions and procedures can be found in Appendix 1.

## Variables

Anticipatory fixations toward each stimulus were recorded between the onset of the sound and the onset of the animation. We calculated fixation time proportion on the to-be-animated Area Of Interest (AOI) for each trial by dividing participants' fixation time on that AOI by their total fixation time on both AOIs. This gaze allocation ratio was used as a dependant variable. A gaze ratio above 0.5 signals more fixations on the animated AOI, while below 0.5 indicates a preference for the non-animated AOI.

Participants' explicit prediction accuracy (1 = predicted that the to-be-animated stimulus was about to move, 0 = predicted that the non-animated stimulus was about to move) was used as a second dependent variable. Absence of answers were coded as NAs. An average explicit prediction score above 0.5 indicates predictions for movement in the animated AOI, while below 0.5 suggests predictions for movement in the non-animated AOI.

The main independent variables were; Group (autistic or non-autistic), Trial (the succession of the 32 trials), Category of trials (standard or oddball). Additionally, core CELF 5 index score was used as an independent variable to measure the effect of participants' general language level on the dependent variables. The General Communication Composite (GCC) index from CCC-2 questionnaire was used as an independent variable to measure the effect of participants' communication abilities on the dependent variables. Participants' vocabulary standard score from WISC-V was used as an independent variable to measure the effect of participants' word knowledge on the dependent variables. And finally, participants' Total IQ score, age and SES were used as control variables to measure the effect of participants' general intelligence, chronological development and socio-economic status on the dependent variables.

To further explore participants' inclination to change their predictive strategy after the oddball trials of the Probabilistic block, we introduced a variable called 'Unfruitful Update Attempt'. This variable is derived from fifteen trials organized into five groups, each comprising three consecutive trials: the trial before the oddball trial, the oddball trial itself, and the trial following it. For instance, group one includes the 6th, 7th (oddball), and 8th trials, while group two comprises the 13th, 14th (oddball), and 15th trials, and so on. The last oddball trial was excluded from the analysis because it was not followed by any subsequent trials. The variable was coded as 1 if the participant accurately predicted the trial before the oddball trial, made an inaccurate prediction during the oddball trial, and another inaccurate prediction during the subsequent trial; otherwise, it was coded as 0. 'Unfruitful Update Attempt' is the sum of 1 per participant and can vary between 0 and 5.

Moreover, to further investigate participants' inclination to predict the outcome based on the pattern of the stimuli during the Dual block, we created a variable called 'Pattern-based prediction'. This variable was coded as 1 if a participant accurately predicted the outcome during the oddball trial, the trial before, and the following trial; otherwise, it was coded as 0. 'Pattern-based prediction' is the sum of 1 per participant and can vary between 0 and 5.

## Analytic Plan

All analyses were conducted using R (R Core Team, 2020). Two sets of analyses were conducted on participants' anticipatory fixations and explicit predictions. First, we used Generalized Additive Models (GAMs) to investigate the nonlinear impact of trials on these variables as well as any potential differences between autistic and non-autistic children regarding their learning curves. Participants' intercept was added as random effect. GAMs were implemented using the mgcv package (version 1.8–40, Wood, 2017).

Second, we sought to determine whether participants attentional exploration and prediction accuracy increased across standard and oddball trials and if that evolution differed between trials' categories and groups. We used Generalized Linear Mixed Models (GLMMs) to analyse the impact of Category (standard or oddball), Group, Trial, and Category X Group and Category X Group X Trial interactions on participants' gaze allocation ratio and prediction accuracy. The models used for the analysis of the Deterministic block did not include the 'Category' variable, as the block exclusively comprises standard trials. Participants' intercept was added as random effect. Generalized Linear Mixed Models (GLMMs) set to beta logistic regression were assessed using the lme4 package (version 2.4, Bates et al., 2015) to analyse participants' gaze allocation ratio, and GLMMs set to binomial logistic regression were assessed to analyse participants' accuracy scores.

The significance of each fixed factor of the GAMs and GLMMs was estimated by running likelihood ratio tests to compare the fit of the model with a model without the factor under consideration, but with an otherwise identical structure (Barr, 2008). We used a stepwise method to compare our models starting from the null model and incrementally augmenting it with the different independent variables, and their interaction, keeping the random structure unchanged, until we reached the theoretically motivated maximal model. We assessed the simple effect of control variables by incorporating them separately as fixed factors into the GLM maximal models and evaluating whether they enhanced the model fit. Post-hoc comparisons of least-square means were carried out on the best-fitting models using the emmeans package (version 1.5.1, Lenth, 2020), with Tukey adjustment for multiple comparisons.

Autistic children showed significantly lower scores in all language indexes compared to non-autistic children (refer to participants' demographic information in Appendix 1). Due to the collinearity effect hindering the interpretation of interactions, separate analyses were conducted for autistic and non-autistic groups to assess the effects of CELF, CCG, and Vocabulary on dependent variables. These analyses were performed individually, concentrating on standard trials in the Probabilistic and Dual blocks, and considering all trials in the Deterministic block. Only participants with complete language indexes were included in these analyses (detailed information on missing data is provided in Appendix 1). When a language variable improved the model fit, we introduced IQ and SES as additional fixed factors to account for its potential influence on the observed relationship. Therefore, we used GLMMs with Vocabulary, CCG, CELF, IQ and SES as fixed effects, and participants' intercepts as random effects.

We investigated the impact of Group on 'Unfruitful Update Attempt' during the Probabilistic block and on 'Pattern-based Prediction' during the Dual block using GLMMs set to Poisson regressions or, in case of overdispersed counts, set to negative binomial regression. The negative binomial regressions were performed using the glm.nb function from the MASS package (version: 7.3–56, Venables, 2022). The effects of language indexes on these variables were investigated by conducting separate analyses for autistic and non-autistic individuals. The fixed effects of Vocabulary, CCG, and CELF were analysed individually.

For clarity and space considerations, only the best-fitting models and significant post-hoc comparisons will be presented in the following section. Full model descriptions are available in Supplementary Material 1.

## Predictions

Based on previously documented precision imbalance in autism, we expected that prediction errors experienced during the Probabilistic block, would lead autistic children to make a higher number of unfruitful update attempts, and therefore provoke less accurate predictions during that block. During the Dual block, we expected that the sound/shape association would initially overshadow the subtle sound/filler pattern association (see, Byrom & Murphy, 2019), and hence lead participants to make prediction errors during the first oddball trials. Additionally, we predicted that these prediction errors would prompt autistic children to explore the stimuli, grasp the predictive value of the subtler sound/filling pattern cue, and update their learning based on that subtle cue more rapidly than non-autistic children.

Finally, we hypothesized positive associations between participants' general language abilities, vocabulary levels, and overall predictive accuracy. Conversely, we predicted a negative correlation between the number of unfruitful update attempts during the Probabilistic block and participants' language indexes.

# Results

## Probabilistic Block

### Gaze

The best-fitting GAM included the Trial smooth effect (LRT (22) = 56.53, $p < .001$); the fitted curve in Fig. 3a shows that anticipatory fixations on the animated stimulus increased between oddball trials and drop during the 1st, 4th, 5th and 6th oddball trials.

The best-fitting GLMM revealed a significant effect of Category ($\chi^2$ (1) = 43.48, $p < .001$); adding participants' total IQ scores as fixed factor significantly improved this model fit ($\chi^2$ (1) = 0.534, $p < .05$), with a positive effect of IQ on gaze ratio ($z = 1.97$, $p < .05$). As illustrated in Fig. 3a, there were higher correct anticipatory fixations during the standard trials compared to the oddball trials, which was confirmed by pairwise post-hoc comparisons ($z = 6.67$, $p < .001$).

## Explicit Prediction

The best-fitting GAM included Trial (LRT (31) = 253, $p < .001$). The fitted curve in Fig. 3b is above 0.5 during the standard trials, which shows that participants correctly predicted the animation of the animated stimulus during these trials. However, the curve drops during each oddball trial and the 95% confidence intervals go well below 0.5 except for the last oddball trial, which is consistent with participants having wrongly anticipated the animation the of the non-animated stimulus during these oddball trials.

The best-fitting GLMM included the Category X Group interaction ($\chi^2$ (1) = 4.53, $p < .05$). Post-hoc pairwise comparisons revealed a greater prediction accuracy during the standard trials compared to the oddball trials ($z = 8.00$, $p < .001$) and a greater Category effect in the non-autistic group compared to the autistic group ($z = 2.13$, $p < .05$). Autistic children displayed lower accuracy during the standard trials compared to non-autistic children ($z$ = -2.83, $p < .05$), but there was no group difference for the oddball trials ($z = 0.17$, $p = .998$); see Fig. 4b for fitted accuracy values.

For the autistic group, stepwise comparisons of GLMMs revealed that the inclusion of Vocabulary, GCC or CELF did

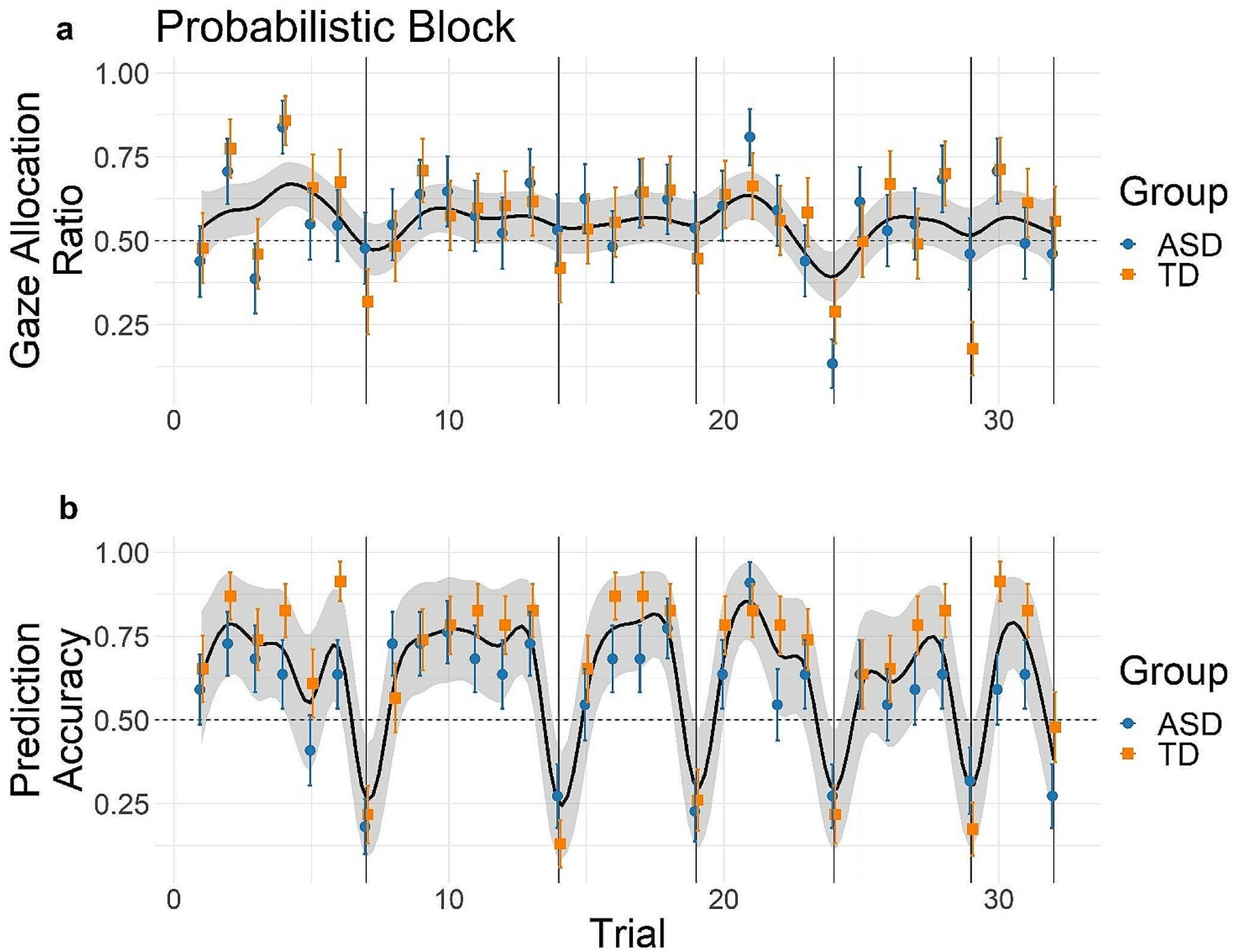


**Fig. 3** Probabilistic block. (**a**) Mean gaze ratios, per trials, by group; vertical lines correspond to Standard Error of Means (SEMs). The line in bold corresponds to fitted gaze ratio adjusted curve, with the shadowed ribbon standing for 95% CIs. (**b**) Mean prediction accuracy, per trials, by group; vertical lines correspond to SEMs. The line in bold corresponds to fitted explicit prediction accuracy adjusted curve, with the shadowed ribbon standing for 95% CIs. Each vertical black line represents an oddball trial

not enhance the model fit (all $p > .378$). Turning to the non-autistic group, stepwise comparisons of GLMMs showed that Vocabulary significantly increased the model fit ($\chi^2$ (1) = 3.94, $p < .05$), while GCC and CELF did not (both $p > .829$). Vocabulary scores had a positive effect on non-autistic participants' explicit predictive accuracy ($z = 2.07$, $p < .05$).

### Unfruitful Update Attempt

Turning to the 'Unfruitful update attempt' variable, stepwise comparisons of GLMMs showed that the inclusion of Group as predictor did not significantly improve the model fit (LR (1) = 0.095, $p = .758$). For both autistic and non-autistic groups, incorporating Vocabulary, GCC, or CELF did not improve the model fit (autistic group: all $p > .088$; non-autistic group: all $p > .277$).

## Deterministic Block

### Gaze

The best-fitting GAM included no smooth terms nor interactions (all $p > .064$) suggesting that the impact of Trial on participants' gaze allocation ratio is linear, and that there are no significant differences between groups regarding these anticipatory gaze curves.

The best-fitting GLMM included no fixed effect or interaction (all $p > .065$), suggesting that participants' gaze ratio did not significantly evolve across trials and that the slopes did not differ between groups. Figure 5a shows that all participants exhibited longer fixations on the to-be-animated stimulus in comparison to the non-animated stimulus during all trials.

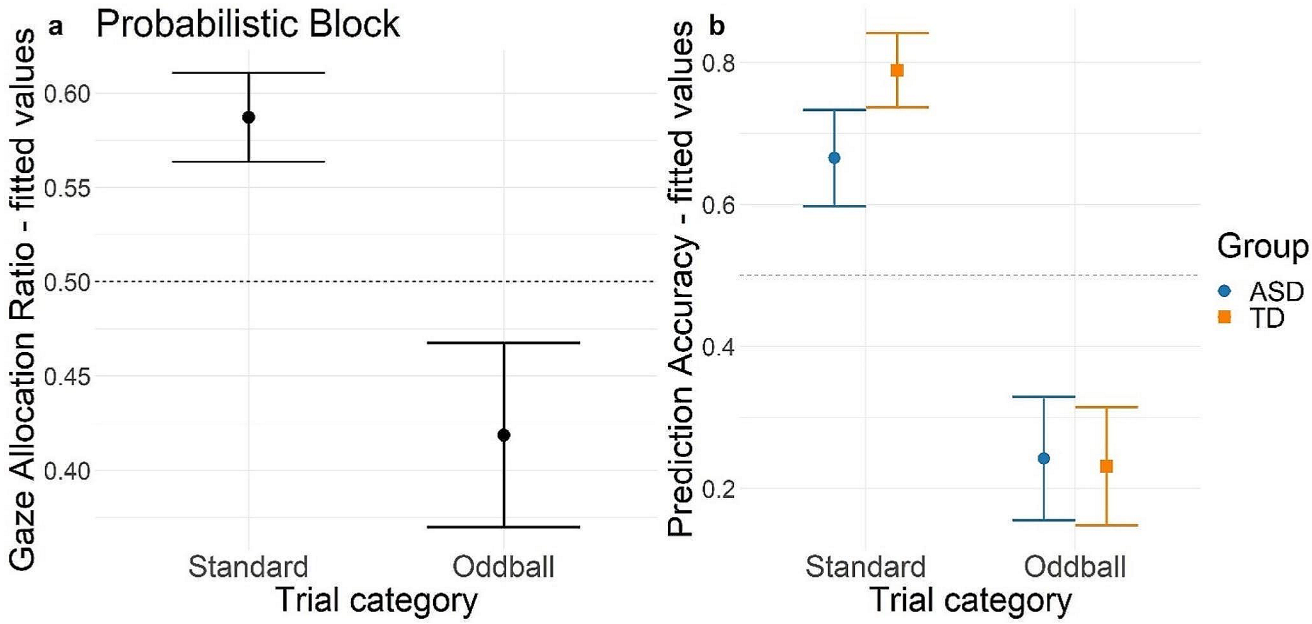


**Fig. 4** Probabilistic block. (**a**) Adjusted mean gaze ratio and 95% CIs by Trial Category. (**b**) Adjusted mean of explicit prediction accuracy and 95% CIs by Trial Category and Group

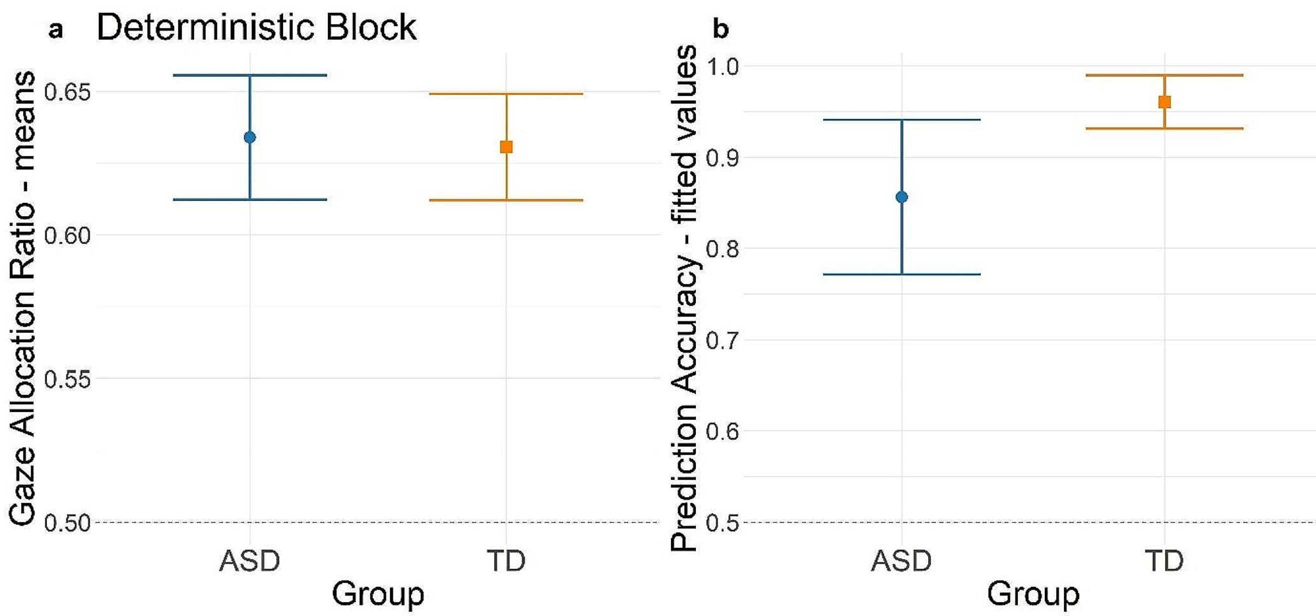


**Fig. 5** Deterministic block. (**a**) Means of gaze ratio by Group. (**b**) Adjusted mean prediction accuracy and 95% CIs by Group

### Explicit Prediction

The best-fitting GAM included no smooth terms nor interactions (all $p > .189$), suggesting that the impact of Trial is linear and that there is no significant difference in participants accuracy curves across trials between groups.

The best-fitting GLMM showed a significant Group effect ($\chi^2$ (1) = 7.29, $p < .01$). Post-hoc pairwise comparisons revealed better prediction accuracy for non-autistic children compared to autistic children ($z = 2.73$, $p < .01$). As shown in Fig. 5b all participants were accurate well above chance, with higher accuracy in the non-autistic participant.

For the autistic group, stepwise comparisons of GLMMs revealed that the inclusion of Vocabulary, GCC, or CELF did not enhance the model fit (all $p > .605$). Turning to the non-autistic group, CELF ($\chi^2$ (1) = 10.18, $p < .01$) improved to model fit while GCC and Vocabulary did not (both $p > .521$). Adding IQ to the best-fitting model (including CELF effect) increased its fit ($\chi^2$ (1) = 6.85, $p < .01$). CELF scores had a positive effect ($z = 3.99$, $p < .001$), and IQ a negative effect ($z$ = -2.66, $p < .01$) on non-autistic participants' explicit predictive accuracy. Adding SES scores to the best-fitting model increased its fit ($\chi^2$ (1) = 7.10, $p < .01$). CELF scores still showed a positive effect ($z = 4.67$, $p < .001$), and SES scores a negative effect ($z$ = -3.05, $p < .01$) on non-autistic participants' explicit predictive accuracy.

## Dual Block

### Gaze

The best-fitting GAM included no smooth terms nor interactions (all $p > .176$) suggesting that the impact of Trial on participants' gaze allocation ratio is linear, and that there are no significant differences between groups regarding these anticipatory gaze curves.

The best-fitting GLMM included Category X Group interaction ($\chi^2$ (1) = 8.97, $p < .01$). Post hoc analyses indicated a greater gaze ratio during the standard trials compared to the oddball trials ($z = 2.61$, $p < .01$), and a greater Category effect in the non-autistic group compared to the autistic group ($z = 3.00$, $p < .01$). However, autistic and non-autistic children' gaze ratios did not differ during the standard ($z$ = -2.18, $p = .13$) or the oddball trials ($z = 2.29$, $p = .10$). Fitted fixation values, along with the 95% CIs are displayed in Fig. 6a: in the standard trials, gaze ratio was significantly above 0.5 for children in both groups. In oddball trials, non-autistic children were well below 0.5, indicating that they predominantly fixated the non-animated stimulus. By contrast, autistics children's gaze ratio was at chance, indicating no overall preference for either AOI.

### Explicit Prediction

The best-fitting GAM included Trial as smooth term (LRT (35) = 453.64, $p < .001$). The curve fitted in Fig. 7 is above 0.5 during the standard trials, showing that participants accurately predicted the animation during these trials. However, the curve drops during each oddball trial and confidence interval set to 95% goes below 0.5, suggesting that participants predicted the animation of the non-animated stimulus during these trials. Importantly, Fig. 7 shows that during the first oddball trial all participants expected the non-animated stimulus to be animated, which confirms a strong spontaneous overshadowing effect of the shape feature of the stimuli over their filling pattern.

The best-fitting GLMM included the Category X Group interaction ($\chi^2$ (1) = 27.56, $p < .001$). Post hoc pairwise comparisons indicated a greater prediction accuracy during the standard trials compared to the oddball trials ($z = 10.21$, $p < .001$) and a greater Category effect in the non-autistic group compared to the autistic group ($z = 5.09$, $p < .001$). Non-autistic children showed better prediction accuracy during the standard trials compared to autistic children ($z = 3.62$, $p < .01$). There was no group difference for the oddball trials ($z = 2.41$, $p = .07$). In sum, all participants exhibited better prediction accuracy during the standard trials compared to the oddball trials and that non-autistic children are better to predict the outcome during the standard trials compared to autistic-children. However, as shown in

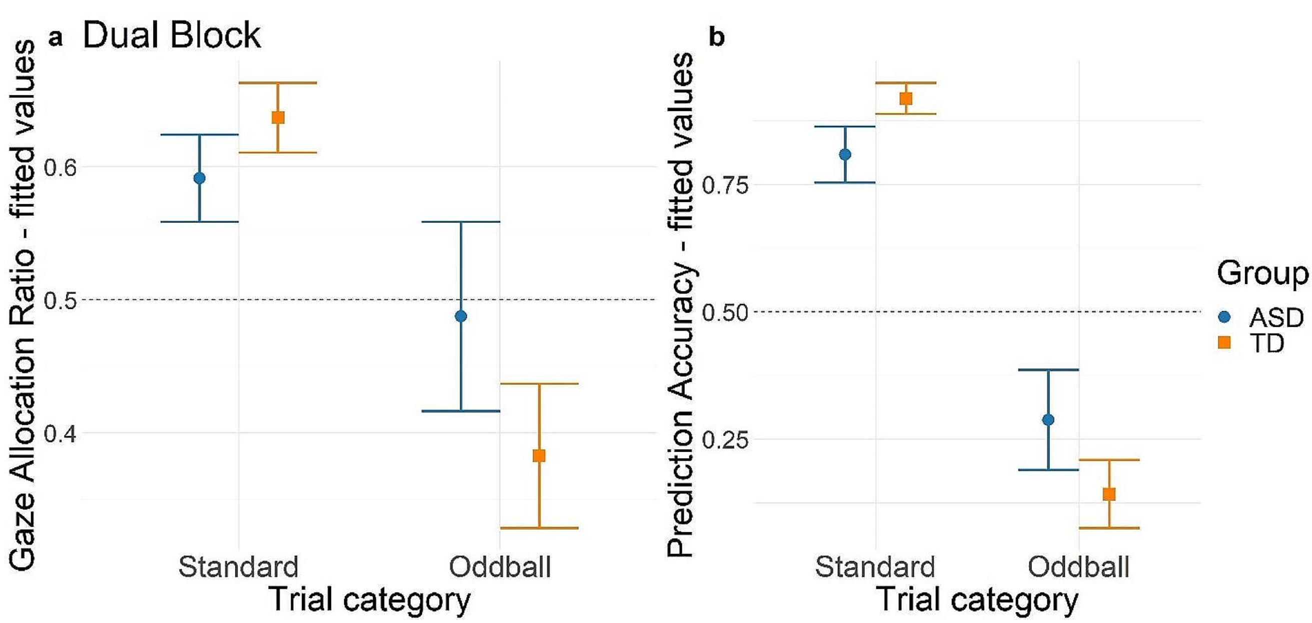


**Fig. 6** Dual block. (**a**) Adjusted mean gaze ratio and 95% CIs by Trial Category and Group. (**b**) adjusted mean prediction accuracy and 95% CIs by Trial Category and Group

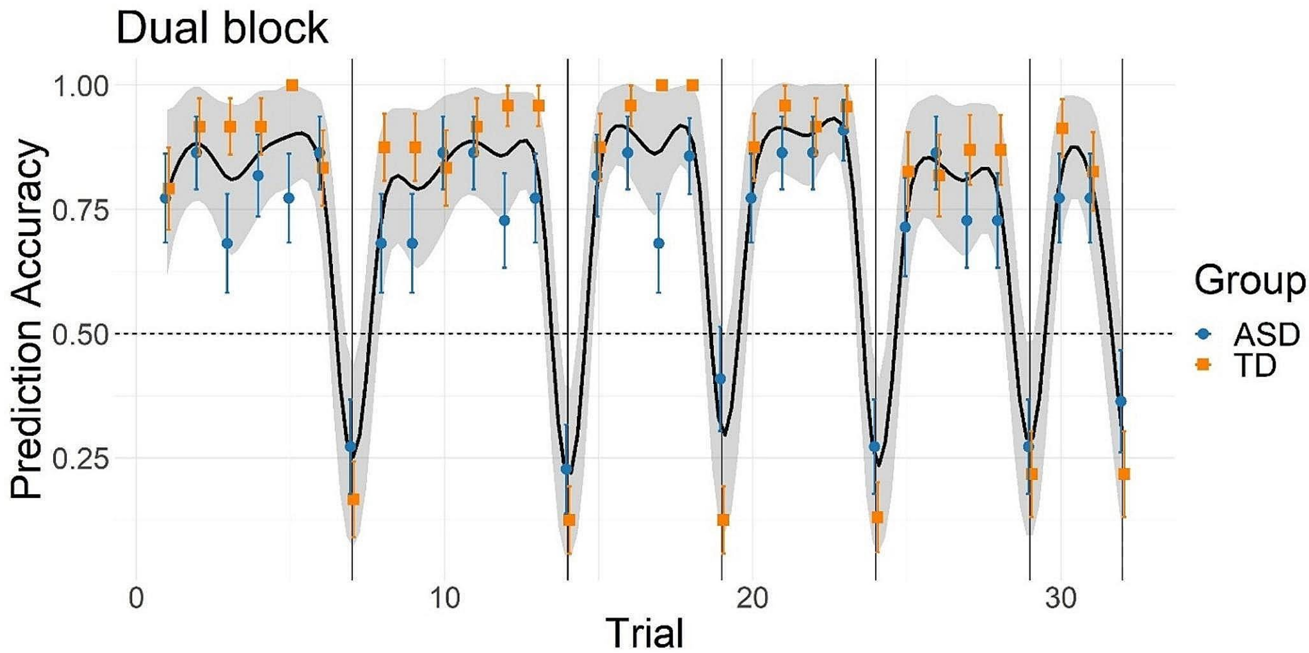


**Fig. 7** Dual block. Mean prediction accuracy, per trials, by group; vertical lines correspond to SEMs. The line in bold corresponds to fitted gaze ratio adjusted curve, with the shadowed ribbon standing for 95% CIs. Each vertical black line represents an oddball trial

Fig. 6b both groups showed the same number of accurate predictions (below 0.5) during the oddball trials.

For the autistic group, GCC or CELF did not enhance the GLMM model fit (all $p>.672$). Turning to the non-autistic group, stepwise comparisons of GLMMs revealed that CELF significantly increased the model fit ($\chi^2$ (1) = 9.51, $p<.01$), while Vocabulary and GCC did not (both $p>.23$). CELF scores had a positive effect on non-autistic participants' explicit predictive accuracy ($z=3.60$, $p<.001$).

### Pattern-based Prediction

Turning to the 'Pattern-based prediction' variable, stepwise comparisons of GLMMs showed that the inclusion of Group as predictor did not significantly improve the model fit (LR (1) = 0.1.30, $p=.255$). For both autistic and non-autistic groups, incorporating Vocabulary, GCC, or CELF did not improve the model fit (autistic group: all $p>.294$; non-autistic group: all $p>. 225$).

## Discussion

Recent predictive coding theories propose that autism involves atypical weighting of prediction errors during learning (Lawson et al., 2017; Palmer et al., 2017; Van de Cruys et al., 2014). It has been suggested that this precision imbalance results in more frequent prior updates in autistic individuals, as compared to their non-autistic peers. We hypothesized that precision imbalance in autism could also yield beneficial effects on learning, particularly in situations where a salient uncertain association coexists with a an overshadowed but more predictive one.

In this study, we investigated anticipatory fixations and explicit predictions made by both autistic and non-autistic children across three associative learning blocks: a Deterministic, a Probabilistic, and a Dual block. The Dual block presented a subtle yet fully predictive cue overshadowed by a less predictive salient one. Based on the precision imbalance theory of autism, we hypothesized that autistic children would demonstrate more unfruitful update attempts in the Probabilistic block, resulting in lower predictive performance in that block. We also expected autistic individuals to benefit from unexpected events in the Dual block, gradually favouring the subtle, yet fully predictive cue. Furthermore, we predicted a positive correlation between participants' language abilities and their overall predictive performance, along with a negative correlation with unfruitful update attempts in the Probabilistic block.

Results from gaze analyses and explicit predictions consistently showed that both autistic and non-autistic children accurately predicted the outcome during the standard trials in all three blocks. Our results also show that participants in both groups expected the non-animated stimulus to move during the oddball trials in the Probabilistic and Dual blocks. Together these results show that both autistic and non-autistic children successfully learned cue-outcome associations, and that they based their predictions on the salient sound-shape association. This bias towards salient and global features during learning diverges from the extensive literature on weak central coherence in autism (Booth & Happé, 2018; Happé & Frith, 2006) and aligns with the perspective of a preserved influence of global information in autism (Van der Hallen et al., 2015). Despite suggestions that such influence in autism requires guided attention (Koldewyn et al., 2013), our findings show a spontaneous preference for global features in autistic children. Although our method involves asemantic sounds rather than words, the spontaneous preference for global features observed in both groups of participants may contrast with studies indicating a preference in autistic children to associate new words with the colour or pattern of referents rather than with the global shapes favoured by non-autistic children (Hupp, 2015; Potrzeba et al., 2015; Tek et al., 2008).

In line with participants' explicit predictions, anticipatory fixations revealed successful cue-outcome associative learning, as well as strong reliance on the salient cue in both the autistic and non-autistic groups. The anticipatory gaze behaviour did not differ between the two groups during the Deterministic and Probabilistic blocks, and participants in both groups made anticipatory fixations on the animated stimulus during the standard trials of the Dual block. However, while non-autistic children showed a clear attentional preference for the non-animated stimulus during the oddball trials of the Dual block, the autistic children's gaze ratio revealed no clear preference between the two stimuli. This finding could suggest reduced associative strength during the Dual block in the autistic group. However, given the clear preference of autistic children for the animated stimulus during standard trials, this result could also imply the detection of pattern change between shapes during oddball trials, resulting in attentional exploration of both stimuli.

Contrary to our hypothesis, autistic children did not make more unfruitful update attempts than non-autistic children during the Probabilistic block. Furthermore, autistic or non-autistic participants do not seem to have achieved a fruitful learning update in favour of the subtle cue at the end of the Dual block, as they did not show a higher number of predictions on the animated stimulus compared to the non-animated stimulus during the final oddball trials. These findings challenge the idea of a greater rate of priors' update due to atypical weighting of prediction errors in autistic versus non-autistic individuals. While this latter hypothesis is supported by studies demonstrating over-adaptation of precision weighing, higher learning rates, and faster learning updates in autistic adults (Allenmark et al., 2021; Goris et al., 2022; Lawson et al., 2017; Sapey Triomphe et al., 2021; Thillay et al., 2016), the literature also includes mixed results, with a growing number of studies reporting no evidence of an overweighting of prediction errors in this population (Pesthy et al., 2023; Rybicki et al., 2021; for reviews see Cannon et al., 2021; Chrysaitis & Seriès, 2023).

A possible explanation for the lack of updates in autistic children in our study could be the absence of reversal contingencies and volatile conditions. It is possible that unexpected events in the Probabilistic and Dual blocks were too predictable, and that the cue-outcome associations were not sufficiently uncertain to induce an overweighting of prediction errors in autistic children (Easdale et al., 2019). The lack of updates in autistic children may also be due to an excessive discrepancy in salience between cues. Although all participants successfully distinguished upside-up and upside-down patterns in an additional the discrimination task (details in Appendix 1), the overshadowing effect of shapes may be too strong to allow participants to capture the predictive value of the subtle cue. Future studies should investigate the impact of salience competition between cues by varying the subtlety of the most predictive cues.

Importantly, even though both autistic and non-autistic participants showed learning across all associative contingencies, autistic children made fewer accurate explicit predictions than their non-autistic peers in all three blocks. As this difference was also observed in the Deterministic block, we cannot attribute it to a difficulty in learning probabilistic associations or to an atypical reaction to prediction errors in autistic children. The first potential explanation is that autistic children show a weaker influence of prior knowledge on predictive processing. In line with this assumption, Greene and colleagues (2019) observed fewer anticipatory fixations on predictive stimuli in autistic adolescents compared to their non-autistic peers during a probabilistic associative learning task. The authors interpreted these findings in light of the hypo-prior accounts of autism (Pellicano & Burr, 2012), which suggest a decrease in prior reliance in autistic individuals. Under this line of analysis, in our study, autistic children may have accurately learned associations but demonstrated a reduced impact of this learnings on their explicit predictions, resulting in hesitant decision-making compared to non-autistic children.

The limited number of trials in each block is another potential explanation for the lower predictive accuracy we observed in our autistic participants. Previous research has shown slower probabilistic learning in autistic compared to non-autistic adults (Solomon et al., 2011). Additionally, category learning and prototype formation have been observed to be slower in autism (Soulière et al., 2011). Therefore, it is possible that autistic children require more trials than non-autistic ones to establish similar associative strength between cue-outcome pairs and create strong and reliable priors.

To the best of our knowledge, no study has directly investigated predictive processing in autistic children through sound-image associations. Therefore, the differences in predictive accuracy between groups observed in our study could result from specific associative learning challenges in autism, such as sound-picture mapping, rather than atypical predictive processing or statistical learning impairment. This interpretation is in line with studies showing atypical word-mapping in autistic children (Hartley et al., 2014, 2019), despite preserved statistical learning abilities (Habeig et al., 2017). Yet, sound-image associations are frequently used to investigate precision imbalance during probabilistic learning in autistic adult (Lawson et al., 2017; Sapey-Triomphe et al., 2021, 2022). Future studies using associative learning tasks to investigate predictive processing should incorporate deterministic designs as control conditions to differentiate associative learning and predictive abilities in autism.

It is worth remembering that although the autistic children made less accurate explicit predictions than non-autistic children, they learned the associations in all the different contingencies. Moreover, no significant difference between autistic and non-autistic children in anticipatory fixations emerged in the Deterministic and Probabilistic blocks. As previously mentioned, these results may indicate a difference between competence and performance in autistic children. Autistic participants may present a spontaneous learning ability as accurate as their non-autistic peers but show reduced performance when explicitly asked to predict outcomes. Lower predictive accuracy in autistic children might result from the inherent symptomatology of autism, such as motor and movement planning issues (Nazarali et al., 2009), potentially leading to difficulties in accurately pressing the correct key despite accurate predictive processing. Such discrepancy between explicit and implicit predictive processing could also result from distinct mechanisms underlying low-level spontaneous predictions and more conscious predictions that involve decision making. Such a distinction merits further investigation.

Finally, contrary to our hypothesis, we found no correlation between the number of update attempts during the Probabilistic block and language indexes in autistic children. This result challenges the idea that atypical language development in autism is linked to a higher rate of unfruitful prior updates during learning. However, in line with our prediction, the vocabulary level of non-autistic participants was positively related with explicit predictions during the Probabilistic block, and CELF scores were positively associated with explicit predictions during the Deterministic and Dual blocks. These findings are line with previous research indicating a positive relation between predictive behaviour and language proficiency in typically developing individuals (Borovsky et al., 2012; Mani & Huettig, 2012).

However, in contrast to prior studies linking predictive gaze processing to language skills in typically developing children (Borovsky et al., 2012; Mani & Huettig, 2012; Reuter et al., 2018, 2019), we found no relationship between participants' language indexes and their anticipatory fixations. Therefore, the observed positive correlation between explicit prediction and language proficiency in non-autistic children may not solely stem from associative learning or predictive performances. It could be attributed to higher-order skills, including metacognitive processing and strategic decision-making, which may be useful in explicit associative learning, essential for advanced language development (Teng, 2022; Teng et al., 2021), but not necessarily engaged in spontaneous gaze anticipation. Surprisingly, language proficiency did not correlate with explicit predictive performances in autistic participants, suggesting potential differences in the underlying mechanisms of language in autism compared to typical development (Kissine et al., 2023). Further research is needed to explore the roles of associative learning and predictive processing in the language development of autistic children.

The strengths of our method are its simplicity and brevity, allowing for reliable data collection with minimal bias from fatigue or inattention. Additionally, this method, combining explicit and implicit predictive behaviours, can easily be extended to various populations, including adults and individuals with other conditions. However, this study has several limitations, two of which have not been discussed yet. Our sample does not represent the entire autism spectrum, limiting generalization to verbal autistic individuals aged 9 to 16. Additionally, our sample size of twenty-three participants per group is rather limited. Addressing these limitations is crucial for future research to enhance the robustness and applicability of our findings.

In conclusion, the study revealed evidence of cue-outcome associative learning in both explicit and implicit measures, along with a strong overshadowing effect of stimulus shape relative to stimulus filling pattern, in both autistic and non-autistic children. Contrary to our predictions, autistic children did not update their associative learning in favour of a subtler but fully predictive cue after experiencing prediction errors. Surprisingly, their explicit predictive performances were lower than those of non-autistic children in both deterministic and probabilistic associative learning tasks. These findings challenge the predictive coding view of autism and underscore the importance of considering autistic performance in sound-image associative learning. Our data also suggest different relations between predictive processing and language proficiency in autistic and non-autistic children.

## Declarations

**Conflicts of Interest** All authors declare that they have no conflicts of interest. This study involved human participants and was approved by the Erasme-ULB Hospital-Faculty Ethics Committee (register number CCB: B4062022000135). Written consent was obtained from all participants and their parents.

## References


Allenmark, F., Shi, Z., Pistorius, R. L., Theisinger, L. A., Koutsouleris, N., Falkai, P., & Falter-Wagner, C. M. (2021). Acquisition and use of 'priors' in autism: Typical in deciding where to look, atypical in deciding what is there. *Journal of autism and developmental disorders*, 1–15.

Amoruso, L., Narzisi, A., Pinzino, M., Finisguerra, A., Billeci, L., Calderoni, S., & Urgesi, C. (2019). Contextual priors do not modulate action prediction in children with autism. _*Proceedings of the Royal Society B*, _286_(1908), 20191319.

Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The autism-spectrum quotient (AQ): Evidence from Asperger syndrome/high-functioning autism, malesand females, scientists and mathematicians. *Journal of Autism and Developmental Disorders*, *31*, 5–17.

Baron-Cohen, S., Richler, J., Bisarya, D., Gurunathan, N., & Wheelwright, S. (2003). The systemizing quotient: An investigation of adults with Asperger syndrome or high–functioning autism, and normal sex differences. *Philosophical Transactions of the Royal Society of London Series B: Biological Sciences*, *358*(1430), 361–374.

Barr, D. J. (2008). Analyzing 'visual world'eyetracking data using multilevel logistic regression. *Journal of Memory and Language*, *59*(4), 457–474.

Bavin, E. L., Kidd, E., Prendergast, L. A., & Baker, E. K. (2016). Young children with ASD use lexical and referential information during on-line sentence processing. *Frontiers in Psychology*, *7*, 171.

Behrens, T. E., Woolrich, M. W., Walton, M. E., & Rushworth, M. F. (2007). Learning the value of information in an uncertain world. *Nature Neuroscience*, *10*(9), 1214–1221.

Bishop, D. V. M. (2003). *Children's communication checklist - Second Edition (CCC-2)*. Pearson.

Booth, R. D., & Happé, F. G. (2018). Evidence of reduced global processing in autism spectrum disorder. *Journal of Autism and Developmental Disorders*, *48*, 1397–1408.

Borovsky, A., Elman, J. L., & Fernald, A. (2012). Knowing a lot for one's age: Vocabulary skill and not age is associated with anticipatory incremental sentence interpretation in children and adults. *Journal of Experimental Child Psychology*, *112*(4), 417–436.

Byrom, N. C., & Murphy, R. A. (2019). Cue competition influences biconditional discrimination. *Quarterly Journal of Experimental Psychology*, *72*(2), 182–192.

Cannon, J., O'Brien, A. M., Bungert, L., & Sinha, P. (2021). Prediction in autism spectrum disorder: A systematic review of empirical evidence. *Autism Research*, *14*(4), 604–630.

Chrysaitis, N. A., & Seriès, P. (2023). 10 years of bayesian theories of autism: A comprehensive review. *Neuroscience & Biobehavioral Reviews*, *145*, 105022.

Church, B. A., Krauss, M. S., Lopata, C., Toomey, J. A., Thomeer, M. L., Coutinho, M. V., & Mercado, E. (2010). Atypical categorization in children with high-functioning autism spectrum disorder. *Psychonomic Bulletin & Review*, *17*, 862–868.

Crawley, D., Zhang, L., Jones, E. J., Ahmad, J., Oakley, B., San José Cáceres, A., & EU-AIMS LEAP group. (2020). Modeling flexible behavior in childhood to adulthood shows age-dependent learning mechanisms and less optimal learning in autism in each age group. *PLoS Biology*, *18*(10), e3000908.

Currie, C., Molcho, M., Boyce, W., Holstein, B., Torsheim, T., & Richter, M. (2008). Researching health inequalities in adolescents: The development of the Health Behaviour in School-aged children (HBSC) family affluence scale. *Social Science & Medicine*, *66*(6), 1429–1436.

Easdale, L. C., Le Pelley, M. E., & Beesley, T. (2019). The onset of uncertainty facilitates the learning of new associations by increasing attention to cues. *Quarterly Journal of Experimental Psychology*, *72*(2), 193–208.

Eigsti, I. M., de Marchena, A. B., Schuh, J. M., & Kelley, E. (2011). Language acquisition in autism spectrum disorders: A developmental review. *Research in Autism Spectrum Disorders*, *5*(2), 681–691.

Friston, K. (2009). The free-energy principle: A rough guide to the brain? *Trends in Cognitive Sciences*, *13*, 293–301. https://doi.org/10.1016/j.tics.2009.04.005.

Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*(2), 127–138.

Friston, K. J., Daunizeau, J., Kilner, J., & Kiebel, S. J. (2010). Action and behavior: A free-energy formulation. *Biological Cybernetics*, *102*, 227–260.

Friston, K., Adams, R. A., Perrinet, L., & Breakspear, M. (2012). Perceptions as hypotheses: Saccades as experiments. *Frontiers in Psychology*, *3*, 151.

Friston, K., FitzGerald, T., Rigoli, F., Schwartenbeck, P., & Pezzulo, G. (2016). Active inference and learning. *Neuroscience & Biobehavioral Reviews*, *68*, 862–879.

Gastgeb, H. Z., & Strauss, M. S. (2012). Categorization in ASD: The role of typicality and development. *Perspectives on Language Learning and Education*, *19*(2), 66–74.

Goris, J., Braem, S., Nijhof, A. D., Rigoni, D., Deschrijver, E., Van de Cruys, S., & Brass, M. (2018). Sensory prediction errors are less modulated by global context in autism spectrum disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *3*(8), 667–674.

Goris, J., Brass, M., Cambier, C., Delplanque, J., Wiersema, J. R., & Braem, S. (2020). The relation between preference for predictability and autistic traits. *Autism Research*, *13*(7), 1144–1154.

Goris, J., Braem, S., Van Herck, S., Simoens, J., Deschrijver, E., Wiersema, J. R., & Todd, J. (2022). Reduced primacy bias in autism during early sensory processing. *Journal of Neuroscience*, *42*(19), 3989–3999.

Greene, R. K., Zheng, S., Kinard, J. L., Mosner, M. G., Wiesen, C. A., Kennedy, D. P., & Dichter, G. S. (2019). Social and nonsocial visual prediction errors in autism spectrum disorder. *Autism Research*, *12*(6), 878–883.

Haebig, E., Saffran, J. R., & Weismer, S. E. (2017). Statistical word learning in children with autism spectrum disorder and specific language impairment. *Journal of Child Psychology and Psychiatry*, *58*(11), 1251–1263.

Happé, F., & Frith, U. (2006). The weak coherence account: Detail-focused cognitive style in autism spectrum disorders. *Journal of Autism and Developmental Disorders*, *36*(1), 5–25.

Hartley, C., & Allen, M. L. (2014). Brief report: Generalisation of word–picture relations in children with autism and typically developing children. *Journal of Autism and Developmental Disorders*, *44*, 2064–2071.

Hartley, C., Bird, L. A., & Monaghan, P. (2019). Investigating the relationship between fast mapping, retention, and generalisation of words in children with autism spectrum disorder and typical development. *Cognition*, *187*, 126–138.

Hestvik, A., Epstein, B., Schwartz, R. G., & Shafer, V. L. (2022). Developmental language disorder as syntactic prediction impairment. *Frontiers in Communication*, *6*, 637585.

Hupp, J. M. (2015). Development of the shape bias during the second year. *The Journal of Genetic Psychology*, *176*(2), 82–92.

Jones, S. D., & Westermann, G. (2021). Predictive processing and developmental language disorder. *Journal of Speech Language and Hearing Research*, *64*(1), 181–185.

Kissine, M., Saint-Denis, A., & Mottron, L. (2023). Language acquisition can be truly atypical in autism: Beyond joint attention. *Neuroscience & Biobehavioral Reviews*, 105384.

Klin, A., Jones, W., Schultz, R., Volkmar, F., & Cohen, D. (2002). Visual fixation patterns during viewing of naturalistic social situations as predictors of social competence in individuals with autism. *Archives of General Psychiatry*, *59*(9), 809–816.

Koldewyn, K., Jiang, Y. V., Weigelt, S., & Kanwisher, N. (2013). Global/local processing in autism: Not a disability, but a disinclination. *Journal of Autism and Developmental Disorders*, *43*, 2329–2340.

Lawson, R. P., Mathys, C., & Rees, G. (2017). Adults with autism overestimate the volatility of the sensory environment. *Nature Neuroscience*, *20*(9), 1293–1299.

Luyster, R. J., Kadlec, M. B., Carter, A., & Tager-Flusberg, H. (2008). Language assessment and development in toddlers with autism spectrum disorders. *Journal of Autism and Developmental Disorders*, *38*, 1426–1438.

Mani, N., & Huettig, F. (2012). Prediction during language processing is a piece of cake—but only for skilled producers. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(4), 843.

Manning, C., Kilner, J., Neil, L., Karaminis, T., & Pellicano, E. (2017). Children on the autism spectrum update their behaviour in response to a volatile environment. *Developmental Science*, 20(5), e12435.

Mottron, L., Bouvet, L., Bonnel, A., Samson, F., Burack, J. A., Dawson, M., & Heaton, P. (2013). Veridical mapping in the development of exceptional autistic abilities. *Neuroscience & Biobehavioral Reviews*, *37*(2), 209–228.

Nazarali, N., Glazebrook, C. M., & Elliott, D. (2009). Movement planning and reprogramming in individuals with autism. *Journal of Autism and Developmental Disorders*, *39*, 1401–1411.

Palmer, C. J., Lawson, R. P., & Hohwy, J. (2017). Bayesian approaches to autism: Towards volatility, action, and behavior. *Psychological Bulletin*, *143*(5), 521.

Pellicano, E., & Burr, D. (2012). When the world becomes 'too real': A bayesian explanation of autistic perception. *Trends in Cognitive Sciences*, *16*(10), 504–510.

Pesthy, O., Farkas, K., Sapey-Triomphe, L. A., Guttengéber, A., Komoróczy, E., Janacsek, K., & Németh, D. (2023). Intact predictive processing in autistic adults: Evidence from statistical learning. *Scientific Reports*, *13*(1), 11873.

Potrzeba, E. R., Fein, D., & Naigles, L. (2015). Investigating the shape bias in typically developing children and children with autism spectrum disorders. *Frontiers in Psychology*, *6*, 446.

Prescott, K. E., Mathée-Scott, J., Reuter, T., Edwards, J., Saffran, J., & Weismer, S. E. (2022). Predictive language processing in young autistic children. *Autism Research*, *15*(5), 892–903.

Rao, R. P., & Ballard, D. H. (1999). Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects. *Nature Neuroscience*, *2*(1), 79–87.

Reuter, T., Emberson, L., Romberg, A., & Lew-Williams, C. (2018). Individual differences in nonverbal prediction and vocabulary size in infancy. *Cognition*, *176*, 215–219.

Reuter, T., Borovsky, A., & Lew-Williams, C. (2019). Predict and redirect: Prediction errors support children's word learning. *Developmental Psychology*, *55*(8), 1656.

Rybicki, A. J., Galea, J. M., Schuster, B. A., Hiles, C., Fabian, C., & Cook, J. L. (2021). Intact predictive motor sequence learning in autism spectrum disorder. *Scientific Reports*, *11*(1), 20693.

Ryskin, R., & Nieuwland, M. S. (2023). Prediction during language comprehension: What is next? *Trends in Cognitive Sciences*, *27*(11), 1032–1052.

Sapey-Triomphe, L. A., Timmermans, L., & Wagemans, J. (2021). Priors bias perceptual decisions in autism, but are less flexibly adjusted to the context. *Autism Research*, *14*(6), 1134–1146.

Sapey-Triomphe, L. A., Weilnhammer, V. A., & Wagemans, J. (2022). Associative learning under uncertainty in adults with autism: Intact learning of the cue-outcome contingency, but slower updating of priors. *Autism*, *26*(5), 1216–1228.

Solomon, M., Smith, A. C., Frank, M. J., Ly, S., & Carter, C. S. (2011). Probabilistic reinforcement learning in adults with autism spectrum disorders. *Autism Research*, *4*(2), 109–120.

Soulières, I., Mottron, L., Saumier, D., & Larochelle, S. (2007). Atypical categorical perception in autism: Autonomy of discrimination? *Journal of Autism and Developmental Disorders*, *37*, 481–490.

Soulières, I., Mottron, L., Giguère, G., & Larochelle, S. (2011). Category induction in autism: Slower, perhaps different, but certainly possible. *Quarterly Journal of Experimental Psychology*, *64*(2), 311–327.

Tek, S., Jaffery, G., Fein, D., & Naigles, L. R. (2008). Do children with autism spectrum disorders show a shape bias in word learning? *Autism Research*, *1*(4), 208–222.

Teng, M. F. (2022). Exploring awareness of metacognitive knowledge and acquisition of vocabulary knowledge in primary grades: A latent growth curve modelling approach. *Language Awareness*, *31*(4), 470–494.

Teng, M. F., & Zhang, L. J. (2021). Development of children's metacognitive knowledge, reading, and writing in English as a foreign language: Evidence from longitudinal data using multilevel models. *British Journal of Educational Psychology*, *91*(4), 1202–1230.

Thillay, A., Lemaire, M., Roux, S., Houy-Durand, E., Barthélémy, C., Knight, R. T., & Bonnet-Brilhault, F. (2016). Atypical brain mechanisms of prediction according to uncertainty in autism. *Frontiers in Neuroscience*, *10*, 317.

Van de Cruys, S., Evers, K., Van der Hallen, R., Van Eylen, L., Boets, B., De-Wit, L., & Wagemans, J. (2014). Precise minds in uncertain worlds: Predictive coding in autism. *Psychological Review*, *121*(4), 649.

Van de Cruys, S., Lemmens, L., Sapey-Triomphe, L. A., Chetverikov, A., Noens, I., & Wagemans, J. (2021). Structural and contextual priors affect visual search in children with and without autism. *Autism Research*, *14*(7), 1484–1495.

Van der Hallen, R., Evers, K., Brewaeys, K., Van den Noortgate, W., & Wagemans, J. (2015). Global processing takes time: A meta-analysis on local–global visual processing in ASD. *Psychological Bulletin*, *141*(3), 549.

van Laarhoven, T., Stekelenburg, J. J., Eussen, M. L., & Vroomen, J. (2020). Atypical visual-auditory predictive coding in autism spectrum disorder: Electrophysiological evidence from stimulus omissions. *Autism*, *24*(7), 1849–1859.

Venker, C. E., Edwards, J., Saffran, J. R., & Weismer, S. E. (2019). Thinking ahead: Incremental language processing is associated with receptive language abilities in preschoolers with autism spectrum disorder. *Journal of Autism and Developmental Disorders*, *49*, 1011–1023.

Wang, L., Schoot, L., Brothers, T., Alexander, E., Warnke, L., Kim, M., & Kuperberg, G. R. (2023). Predictive coding across the left fronto-temporal hierarchy during language comprehension. *Cerebral Cortex*, *33*(8), 4478–4497.

Ward, E. K., Braukmann, R., Weiland, R. F., Bekkering, H., Buitelaar, J. K., & Hunnius, S. (2021). Action predictability is reflected in beta power attenuation and predictive eye movements in adolescents with and without autism. *Neuropsychologia*, *157*, 107859.

Wechsler, D. (2014). *Wechsler Intelligence Scale for Children - Fifth Edition*. WISC-V). Pearson.
Weismer, S. E., & Kover, S. T. (2015). Preschool language variation, growth, and predictors in children on the autism spectrum. *Journal of Child Psychology and Psychiatry*, *56*(12), 1327–1337.
Weismer, S. E., & Saffran, J. R. (2022). Differences in prediction may underlie language disorder in autism. *Frontiers in Psychology*, *13*, 897187.
Wiig, E. H., Semel, E., & Secord, W. (2013). Clinical Evaluation of Language Fundamentals - Fifth Edition (CELF-5). Pearson.
Wittke, K., Mastergeorge, A. M., Ozonoff, S., Rogers, S. J., & Naigles, L. R. (2017). Grammatical language impairment in autism spectrum disorder: Exploring language phenotypes beyond standardized testing. *Frontiers in Psychology*, *8*, 532.
Wodka, E. L., Mathy, P., & Kalb, L. (2013). Predictors of phrase and fluent speech in children with autism and severe language delay. *Pediatrics*, *131*(4), e1128–e1134.
Ylinen, S., Bosseler, A., Junttila, K., & Huotilainen, M. (2017). Predictive coding accelerates word recognition and learning in the early stages of language development. *Developmental Science*, 20(6), e12472.
Yoon, C. D., Xia, Y., Terol, A. K., Meadan, H., & Lee, J. D. (2024). Correlation between gaze behaviors and Social Communication Skills of Young Autistic Children: A Meta-analysis of Eye-Tracking studies. *Journal of Autism and Developmental Disorders*, 1–19.
Zhou, P., Zhan, L., & Ma, H. (2019). Predictive language processing in preschool children with autism spectrum disorder: An eye-tracking study. *Journal of Psycholinguistic Research*, *48*, 431–452.

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