Suboptimal but intact integration of Bayesian components during perceptual decision-making in autism

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AY, BS.H and RD, conceptualized and designed the study. LF conducted and collected the data. LF, AY, and RD analyzed the data. The original draft was written by LF and reviewed by all authors.

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Abstract

Alterations in sensory perception, a core phenotype of autism, are attributed to imbalanced integration of sensory information and prior knowledge during perceptual statistical (Bayesian) inference. However, empirical investigations have yielded conflicting results with evidence remaining limited. Critically, previous studies did not assess the independent contributions of priors and sensory uncertainty to the inference process and largely overlooked another Bayesian component: reward. We addressed this gap by quantitatively assessing both the independent and interdependent contributions of priors, sensory uncertainty, and reward to perceptual decision-making in autistic and non-autistic individuals (N=145) during an orientation categorization task. Contrary to common views, autistic individuals integrated all Bayesian components into their decision behavior, and did so indistinguishably from non-autistic individuals. Both groups adjusted their decision criteria in a suboptimal manner. These results reveal intact inference for autistic individuals during perceptual decision-making, challenging the notion that Bayesian computations are fundamentally altered in autism.

Significance statement

Prevailing theories suggest that sensory alterations in autism result from impaired Bayesian computations. However, empirical studies have produced inconsistent results, had confounding factors, and only partially tested the Bayesian proposal. Here, we rigorously tested this proposal using a large sample size (N=145), extensive testing of each participant to measure full psychometric functions, and independent experimental manipulation of each component of Bayesian decision theory: prior, sensory uncertainty, and reward. Quantitative modeling and comparisons to optimal observers revealed that both autistic and non-autistic individuals incorporate all Bayesian components in a similarly suboptimal manner. These findings of intact perceptual decision computations in autism suggest that Bayesian theories of autism must be revisited. They also have practical, occupational implications for individuals with autism.

Main Text

In acknowledgment of the ongoing discourse regarding terminology about individuals diagnosed with autism, we use "autistic individuals" and “non-autistic individuals” in line with recent conventions.

Introduction

Autism Spectrum Disorder is a group of neurodevelopmental disorders with an unknown etiology. Although autism encompasses a wide range of symptoms, it is primarily characterized by atypical social cognitive capacities, such as theory of mind and cognitive empathy(1). Recently, there has been growing interest in sensory processing in autism as a core phenotype(2, 3). Despite evidence demonstrating sensory symptoms and perceptual alterations in autistic people(4, 5), whether and how a single mechanism can explain the various symptoms of autism remains unknown.

In the effort to explain this variety of phenotypes, two related theoretical frameworks, Bayesian inference and predictive coding, suggested an underlying mechanistic account involving canonical processes of perceptual inference(6). In both frameworks, perception is the outcome of inference processes that combine noisy external (sensory) information with internal models of the world. Bayesian inference is a computational framework in which sensory uncertainty (likelihood) and internal models (priors) are combined according to Bayes' rule(7, 8) (**Fig. 1a**). Predictive coding provides a neural implementation of this integration process, which is not necessarily Bayesian(6, 9–11). As an example of how these theoretical frameworks have explained perception, consider the following scenario: You see a large, shadowy figure during a night walk outside your home. If you live in some parts of North America, you know that bears live nearby. If you live in some parts of the Middle East, you know that boars live nearby. Because here the sensory information (likelihood) is uncertain, prior beliefs about the probability of encountering a boar or a bear would make a Bayesian observer more likely to categorize the shadowy figure as the animal that lives nearby than the one that lives on a different continent.

According to these theoretical frameworks, altered perception in autism arises from reduced use of prior beliefs. The Bayesian account postulates that difficulties in extracting prior information from the perceptual environment(12) or enhanced sensory evidence(13–15) could lead to an underuse of prior information in autism. The predictive coding view assumes an inflexibility to adjust prediction errors when sensory input deviates from expectations(16–18).

Despite the popularity of these views, which we collectively refer to as the altered integration hypothesis, evidence remains inconclusive(3, 19) and often depends on post hoc interpretations of results rather than the experimental manipulation of Bayesian components(3). As a result, observed alterations in perceptual inference may reflect alterations in priors, sensory uncertainty, or the integration of the two.

The inconsistent findings could also stem from experimental shortcomings—such as inadequate prior learning attributable to compromised attentional or working memory capacities in autism(3, 19) (i.e., impaired learning of priors)—rather than a genuine reduced effect of priors(20, 21) (i.e., altered integration process). Moreover, studies often do not distinguish between different types of priors, such as natural (e.g., light from above(22)) vs. learned priors(18) or implicit (e.g., regression to the mean(23)) vs. explicit priors (e.g., base rate knowledge of wildlife in your area).

Finally, a third component critical for optimal behavior in Bayesian models is the reward (or cost function)(24). For example, the expected cost of misidentifying a bear also guides the perceptual decision-making process under a Bayesian framework. Outside of the Bayesian framework, studies that investigated reward sensitivity in autism have suggested that autistic participants might exhibit reduced sensitivity to reward(25–27). However, most Bayesian investigations have primarily focused on the effect of priors, thus failing to assess differences that may arise from the integration of either sensory uncertainty or reward. Thus, it remains unclear whether autistic individuals are truly impaired in prior integration or in the integration of other Bayesian components. Addressing these questions is critical to determine whether impairments in Bayesian inference constitute a core computational deficit in autism.

Here, we directly tested the altered integration hypothesis by systematically manipulating and testing the impact of each Bayesian component on perceptual decision-making. We used signal detection theory (SDT)—a standard model of decision-making and a special case of Bayesian inference—to estimate perceptual sensitivity and decision boundaries used to make categorical perceptual decisions. We manipulated priors (Experiment 1), reward (Experiment 2), and sensory uncertainty (Experiment 3) to directly assess the contribution of each Bayesian component to the decision boundary in autistic vs. non-autistic groups. This approach disentangled the effect of priors from sensory uncertainty and incorporated reward into a unified experimental design. Importantly, explicit priors were given, allowing us to independently test and rule out differences between groups in prior learning. Stimulus contrast was manipulated to control for performance level, and the effectiveness of the prior and reward manipulations was assessed to ensure task comprehension and motivation. Under these tightly controlled conditions, we found that autistic individuals incorporate each Bayesian component into their perceptual decisions in a comparable manner to non-autistic controls, providing evidence against the altered integration hypothesis in autism.

Results

A total of 52 autistic and 93 non-autistic adults participated in this study. In all experiments, participants categorized the orientation of grating stimuli presented at the center of the screen (**Fig. 1b**). In each trial, the stimulus was drawn from one of two categories with Gaussian distributions over orientation(28–30). In Task 1, designed to test prior and reward (Experiments 1 and 2), orientations were drawn from partially overlapping Gaussian distributions with means $m_A = -4^\circ$ (Category A) and $m_B = 4^\circ$ (Category B) and standard deviations $s_A = s_B = 5^\circ$ (**Fig. 1c**, **Task 1**). Here, we expected a shift of decision boundary that favored the category with the high base rate/reward (**Fig. 1d**, **Task 1**). Because in Task 1, participants have no incentive to adjust their categorical decision boundaries in response to changes in sensory uncertainty alone(30), we used the embedded category task (Task 2) in Experiment 3. In Task 2, orientations were drawn from embedded Gaussian distributions with means $m_A = m_B = 0^\circ$, and standard deviations $s_A = 3^\circ$ (Category A) and $s_B = 12^\circ$ (Category B) (**Fig. 1c, Task 2**). In this task, we expected the decision boundaries to shift outwards as the sensory uncertainty increased (**Fig. 1d**, **Task 2**). Stimulus contrast was varied across seven values to control for performance level and to manipulate sensory uncertainty.

1. Experiment 1: Intact integration of prior information

Thirty-four autistic and 49 non-autistic individuals participated in Experiment 1. We excluded 3-4 autistic and 3-4 non autistic participants from the analysis. Participant recruitment data and exclusion criteria for all experiments are detailed in the Methods section (**Data analyses**, **Outlier removal**, and **Table 1**).

Here, we tested the effect of prior knowledge on decision criterion. To manipulate priors, we varied the base rate probability of the two categories across blocks. On a given block of trials, category B could appear with a lower (25%), equal (50%), or higher (75%) base rate probability compared to category A.

To test whether participants adopted the appropriate base rate, at ten random times during each block, participants were asked to gamble on the category of the upcoming trial by placing a bet that divided 100 points between the two categories.

Prior manipulation verification

Both autistic and non-autistic groups adjusted their gambling behavior in response to the base rate manipulation. An Analysis of Variance (ANOVA) on the average amount gambled on categories A and B showed a significant effect of base rate (**Fig. 2a)** ($F(2, 144) = 122.38$, $p < .001$, $\eta_p^2 = .63$) with higher gambling points on the category with the higher base rate. We did not find a main effect of group (autistic vs. non-autistic, $F(1, 72) = 0.92$, $p = .342$, $\eta_p^2 = .01$), nor an interaction between group and base rate ($F(2, 144) = .52$, $p = .598$, $\eta_p^2 < .01$). These findings suggest that both participant groups understood the manipulation of the base rate to a similar degree.

Categorization task

Category reports

Figs. 2b-c illustrate, for each group, the probability of reporting Category B as a function of orientation. We observed a characteristic sigmoid shape with a higher probability of reporting Category B as the stimulus was oriented more clockwise (toward positive values). Category B reports increased, with an upward shift of the psychometric function, when there was a high base rate for Category B, and decreased (downward shift) when there was a low base rate for Category B. This shift of probability was supported by an ANOVA, showing a main effect of block on the probability of reporting Category B. $F(1.45, 109.08) = 62.15$, $p <.001$, $\eta_p^2 = .45$. Overall, the pattern of results is comparable across groups.

Perceptual sensitivity

Perceptual sensitivity for orientation categorization increased with contrast for both groups, confirming that the manipulation of stimulus strength was effective. An ANOVA on sensitivity (*d'*) showed a significant main effect of contrast level, $F(6, 450) = 151.82$, $p < .001$, $\eta_p^2 = .67$ **(Fig. 3a).** There was no main effect of group, $F(1, 75) = 2.20$, $p = .142$, $\eta_p^2 = .03$. However, there was a significant interaction between group and contrast level, $F(6, 450) = 2.29$, $p = .034$, $\eta_p^2 = .03$. Post-hoc t-tests revealed that this interaction stemmed from greater sensitivity in the non-autistic group compared to the autistic group at two contrast levels: 0.016 ($t(198) = 2.92$, $p = .004$) and 0.033 ($t(162) = 3.34$, $p = .001$). The effects of base rate bocks and the interaction between base rate and contrast levels are detailed in the **Supplementary Results 1**. Finally, the t-test Bayes factor estimating the likelihood of the alternative hypothesis assuming a difference in sensitivity between groups (H1) over the null hypothesis assuming no difference between groups (H0) provided weak evidence for the alternative hypothesis ($BF_{10} = 1.59 \pm 0.01\%$). Whereas some have proposed that greater sensory precision in autism reduces the use of prior information, here we found, if anything, reduced perceptual sensitivity for the autistic group.

Decision boundaries

Decision boundaries determine whether a stimulus orientation will be categorized as coming from category A or B. To quantify how the decision boundary shifts with prior information about category base rate, we computed the decision criterion for each base rate block and contrast level (**Figs. 3b-c**) and calculated the criterion shift ($\Delta_{criterion}$) as the shift between the two biased base-rate conditions (25% and 75%). An ANOVA showed a significant effect of contrast level on $\Delta_{criterion}$, $F(6, 450) = 60.49$, $p < .001$, $\eta_p^2 = 0.45$, indicating that the criterion shift increased as contrast decreased (**Fig. 3d**), consistent with the Bayesian prediction of greater reliance on the prior when sensory information is more uncertain. There was no effect of group, $F(1, 75) = 0.99$, $p = .321$, $\eta_p^2 < .01$. The interaction between group and contrast level was significant, $F(6, 450) = 2.12$, $p = .05$, $\eta_p^2 = .03$, and post-hoc t-tests revealed that at contrast 0.033, autistic participants showed a significantly greater criterion shift than non-autistics, $t(46.8) = 2.37$, $p = .022$. The Bayes factor ($BF_{10} = 0.38 \pm 0.05\%$) supported the evidence for the null hypothesis assuming no difference in criteria shift between groups. Overall, autistic and non-autistic participants adjusted their decision criterion in response to the prior manipulation.

Optimal observer analyses

To assess criterion shift while controlling for variations in sensitivity, we compared the observed *c* shift to the shifts expected for an optimal observer. For each individual, at each contrast level and biased base rate condition, we calculated the deviation from optimality (c_{error}) values by subtracting the observed criterion from the optimal criterion (see **Methods**, **Data analyses**). The further from zero, the more participants' criterion deviated from an optimal observer. An ANOVA on the c_{error} showed a significant main effect of contrast level on c_{error}, $F(6, 438) = 29.61$, $p < .001$, $\eta_p^2 = 0.29$ **(Fig. 3e).** Participants demonstrated larger c_{error} as contrasts decreased, indicating a more suboptimal shift when sensory evidence was weaker. Critically, there was no effect of group, $F(1, 73) = 0.04$, $p = .851$, $\eta_p^2 < .01$, and no interaction between group and contrast level, $F(6, 438) = 0.41$, $p = .873$, $\eta_p^2 < .01$. The results of the ANOVA were supported by the Bayes factor ($BF_{10} = 0.07, \pm 0.27\%$), providing strong evidence for H0 (i.e., no difference in suboptimality between groups). These results indicate that, when perceptual sensitivity is taken into account, autistic individuals adjust their criteria in the same suboptimal manner as non-autistic individuals: both groups deviate more from an optimal observer as sensory evidence decreases. This finding contradicts the altered integration hypothesis in autism.

2. Experiment 2: Intact integration of reward information

Previous studies showing reduced sensitivity to social and non-social rewards(25–27) imply a potential alteration in integrating reward information during decision-making. Such alterations may explain the reduced effect of context on perception and behavior. However, no study has directly tested the impact of reward on perceptual decision boundaries in autism. In Experiment 2, we address this question by assessing the effect of a monetary reward manipulation on the same orientation categorization task (Task 1) used in Experiment 1.

To manipulate the reward, we varied the points awarded for correct answers across three blocks of trials. In the unbiased reward block, each correct response was awarded 2 points. In the two biased reward blocks, a correct response was awarded 3 points for one category and 1 point for the other. Specifically, in one biased block, category A was awarded 3 points, while in another biased reward block, category B was awarded 3 points. The order of the biased reward blocks was counterbalanced. To confirm that participants understood the reward manipulation, participants were periodically asked to predict the number of points they would receive for a correct response if they chose a specific category in the next trial.

Thirty-two autistic and 48 non-autistic participants took part in Experiment 2. Two autistic and 4-6 non-autistic participants were excluded from data analyses (see **Methods**).

Reward manipulation verification

First, we observed a very high accuracy in performing the excepted reward question, for both non-autistic, *m* = .871, *se* = .267, and autistic participants, *m* = .852, *se* = .319, with no difference between the groups $F(1, 72) = 0.10$, $p = .478$, $\eta_p^2 < .01$ (**Fig. 4a**). Then, to assess whether participants understood our reward manipulation, we conducted an ANOVA on the expected number of reward points as reported by participants in response to the manipulation test questions. This analysis confirmed that both groups similarly comprehended the point values in the reward manipulation. Specifically, there was a significant effect of reward block on the number of points participants expected for each category, $F(2, 144) = 198.02$, $p < .001$, $\eta_p^2 = .73$, and there was no main effect of group, $F(1, 72) = 3.39$, $p = .070$, $\eta_p^2 = .05$. Furthermore, the interaction between group and reward block was not significant, $F(2, 144) = 1.38$, $p = .254$, $\eta_p^2 = .02$ (**Fig. 4b**). These results confirm that both groups understood well and to the same extent the reward manipulation.

Categorization task

Category reports

Figs. 4c-d illustrates, for each group, the probability of reporting Category B as a function of orientation. As in Experiment 1, the probability of reporting Category B increased as the stimulus was oriented more clockwise (toward positive values). Category B reports increased, with an upward shift of the psychometric function, when there was a higher reward for Category B, and decreased (downward shift) when there was a lower reward for Category B. This pattern was supported by an ANOVA showing a main effect of block on the probability to report Category B, $F(1.20, 86.35) = 21.59$, $p < .001$, $\eta_p^2 = .23$. Overall, the pattern of results is comparable across groups.

Perceptual sensitivity

Perceptual sensitivity to the orientation category increased with contrast similarly for both groups. An ANOVA on *d'* showed a significant effect of contrast level on *d'*, $F(6, 432) = 184.19$, $p < .001$, $\eta_p^2 = .72$ (**Fig. 5a**). There was no effect of group, $F(1, 72) = .39$, $p = .534$, $\eta_p^2 < .01$, nor an interaction between group and contrast level, $F(6, 432) = .48$, $p = .824$, $\eta_p^2 < .01$, and the main effect of reward block was not significant ($F(2, 144) = 2.46$, $p = .089$, $\eta_p^2 = .03$). These results are aligned with Experiment 1, indicating that autistic and non-autistic participants show comparable sensitivity to the category distributions across contrasts. The interaction between group and reward block was significant, $F(2, 144) = 3.29$, $p = .040$, $\eta_p^2 = .04$, and arises from an effect of group that is close to significance in the reward block "B = 1 point", $F(1, 516) = 3.64$, $p = .057$, $\eta_p^2 < .01$, but not in the reward blocks "B = 2 points", $F(1, 516) = .81$, $p = .370$, $\eta_p^2 < .01$, or "B = 3 points", $F(1, 516) = 1.05$, $p = .306$, $\eta_p^2 < .01$ (**Fig. 5b**). The interaction between reward block and contrast, $F(12, 864) = 3.56$ $p < .001$, $\eta_p^2 = .05$, and the three-way interaction between group, reward block, and contrast, $F(12, 864) = 2.29$, $p = .007$, $\eta_p^2 = .03$, were significant (see **Supplementary Results 2**). The Bayes factor ($BF_{10} = 0.10 \pm 0.22\%$) provided strong evidence supporting the null hypothesis of no difference in sensitivity between the groups.

Decision boundaries

Decision boundaries reflected the reward manipulation, with a shift of criterion driven by the reward block in both groups (**Figs. 5c-d**). Autistic and non-autistic participants adopted comparable decision criterion shifts $\Delta_{\text{criterion}}$ in response to varying rewards. An ANOVA on the $\Delta_{\text{criterion}}$ revealed a main effect of contrast level, $F(6, 432) = 13.10$, $p < .001$, $\eta_p^2 = .15$, demonstrating that both groups exhibited a larger shift of criterion as contrasts decreased (**Fig. 5e**). There was no effect of group, $F(1, 72) = .03$ $p = .87$, $\eta_p^2 < .01$, and the interaction between group and contrast level was not significant, $F(6, 432) = .35$ $p = .91$, $\eta_p^2 < .01$. These results were supported by the Bayes factor ($BF_{10} = 0.10 \pm 0.16\%$) providing strong evidence in favor of the null hypothesis assuming no difference between groups. These results show that both autistic and non-autistic participants adjust their criteria to favor a more rewarding category, and they adjust more when sensory evidence is weaker, consistent with the Bayesian prediction.

Optimal observer analyses

We next assessed how autistic and non-autistic participants adjusted their decision behavior in response to changing rewards, taking into account their perceptual sensitivity. An ANOVA conducted on c_{error} revealed a significant effect of contrast level, ($F(6, 420) = 36.52$, $p < .001$, $\eta_p^2 = 0.34$), with greater deviation from the optimal criterion as contrast decreased (**Fig. 5f**). Notably, there was no main effect of group, $F(1, 70) = .005$, $p = .94$, $\eta_p^2 < .01$, and the interaction between group and contrast level was not significant, $F(6, 420) = .30$, $p = .94$, $\eta_p^2 < .01$. The Bayes factor ($BF_{10} = 0.07 \pm 28\%$), providing evidence for the null hypothesis assuming no difference between groups in suboptimality, supported the ANOVA's findings. The significant increase in c_{error} as contrast decreased indicates that both groups adjusted their decision criterion in a more suboptimal manner as sensory evidence weakened, and they did so to a similar extent. We therefore find evidence for intact integration of a reward during perceptual decision-making in autism.

3. Experiment 3: Intact integration of sensory uncertainty

The results of Experiments 1 and 2 demonstrate that autistic participants adjusted their decision criterion in response to changes in priors and reward information in a typical though suboptimal manner. Suboptimality in these tasks could arise from inadequate use of priors and rewards, or inadequate assessments of the observer's own sensory uncertainty, and the contributions of these two factors could differ across autistic and non-autistic participants. To distinguish between these possibilities, in Experiment 3 we asked whether autistic individuals could adjust their decision rules to take into account variations in their own sensory uncertainty, separate from prior and reward manipulations. This experiment thus isolates the third Bayesian component, the likelihood function, to determine whether and how autistic participants account for changes in their own sensory uncertainty during perceptual decision-making.

To isolate the contribution of sensory uncertainty to decision-making, we used a task in which changes in sensory uncertainty alone require an adjustment in decision rules to maximize task performance. Participants performed an embedded category task(28–30) (see **Fig. 1c**, **Task 2**) in which they were asked to distinguish between a broad category of orientation and a narrow one. Sensory uncertainty was manipulated by varying the stimulus contrast trial by trial. Integration of sensory uncertainty information in the decision-making process would be evident if decision boundaries shifted outward as sensory uncertainty increased (**Fig. 1d**, **Task 2**).

Thirty-four autistic and 44 non-autistic people participated in Experiment 3. Seven autistic and 4-6 non-autistic participants were excluded from the analyses (see **Methods**).

Category reports

Figs. 6a-b illustrates, for each group, the probability of reporting Category B as a function of orientation. Using the embedded category task (Task 2), the probability of reporting Category B (with the wider distribution) increased as the stimulus was oriented away (clockwise or counterclockwise) from horizontal (0°; see **Fig. 1d**, **Task 2**). For both groups, category reports became more sensitive to stimulus orientation as contrast increased. These observations were supported by the ANOVA showing a main effect of contrast on the probability to report Category B, $F(3, 189.11) = 31.47$, $p < .001$, $\eta_p^2 = .33$.

Perceptual sensitivity

Increasing contrast led to lower sensory uncertainty, as estimated by an SDT-style model adapted to the embedded category task (see **Methods**), consistent with the expected effect of contrast in improving orientation information. The ANOVA conducted on the parameter σ of the model, which provided an estimate of sensory uncertainty, revealed a significant main effect of contrast level $F(6, 390) = 46.03$, $p < .001$, $\eta_p^2 = .42$), confirming that the manipulation of contrast induced a change in sensory uncertainty (**Fig. 7a**). There was no significant difference between groups $F(1, 65) = .07$, $p = .794$, $\eta_p^2 < .01$), nor an interaction between group and contrast $F(6, 390) = .39$, $p = .887$, $\eta_p^2 < .01$. These results were supported by the Bayes factor ($BF_{10} = 0.11 \pm 0.15\%$) providing evidence for the null hypothesis (i.e., no difference in sensitivity between groups). These findings suggest that both groups exhibited similar changes in sensitivity in response to the contrast manipulation in the embedded category task.

Decision boundaries

Participants' categorical decision boundaries depended on contrast (**Figs. 6a-b**). Both groups shifted their categorical decision boundaries outward as sensory uncertainty increased, the qualitative pattern expected from a Bayesian observer (**Figs. 7b-d**). The ANOVA conducted on the *k* parameter of the model, which provides an estimate of the category boundaries, revealed a significant main effect of contrast $F(6, 390) = 38.56$, $p < .001$, $\eta_p^2 = .37$, indicating that the participant's decision boundaries were sensitive to the sensory uncertainty manipulation. Notably, there was no significant effect of group ($F(1, 65) = .03$, $p = .858$, $\eta_p^2 < .01$), nor an interaction between group and contrast, $F(6, 390) = .59$, p

= .741, $\eta_p{}^2 < .01$). The Bayes factor $BF_{10} = 0.11 \pm 0.16\%$) provided strong evidence for the null hypothesis (i.e., no difference in criteria shift between groups), supporting the ANOVA's results. These results indicate that both groups adjusted their decision boundaries similarly in response to changes in sensory uncertainty.

Suboptimality

Next, we asked how much the decision boundary shifts in autistic and non-autistic participants deviated from those of an optimal Bayesian observer (**Fig. 7c**). The ANOVA conducted on k_{error} revealed a significant main effect of contrast $F(6, 378) = 11.06$, $p < .001$, $\eta_p{}^2 = 0.15$, with a greater deviation from the optimal decision boundaries when contrast was lower. There was no significant difference between groups, $F(1, 63) = .16$, $p = .688$, $\eta_p{}^2 < .01$) and no significant interaction between group and contrast, $F(6, 378) = 2.10$, $p = 0.053$, $\eta_p{}^2 = .03$. These results were supported by the Bayes factor ($BF_{10} = 0.13 \pm 0.13\%$) providing strong evidence for the null hypothesis (i.e., no difference in suboptimality between groups). These results show that during perceptual decision-making, autistic individuals take sensory uncertainty into account similarly to the non-autistic group.

Discussion

We conducted a series of experiments to investigate Bayesian inferences in visual perceptual decision-making in autistic individuals and non-autistic controls. In these experiments, participants performed an orientation categorization task, while we separately manipulated category base rate, category reward, and sensory uncertainty. In a Bayesian framework, these manipulations would induce changes in each Bayesian decision component: prior knowledge, reward, and sensory uncertainty respectively. This study reveals that, despite some differences in sensitivity to orientation information, the autistic group adjusted their decision criterion to accommodate variations in priors, reward information, and sensory uncertainty, in a manner comparable to the suboptimal adjustments of the non-autistic group. Autistic participants are intact in incorporating each Bayesian component into their perceptual decisions. These results prompt a reevaluation of the altered integration hypothesis.

Perceptual Priors

The altered integration hypothesis, despite a lack of direct evidence, remains prevalent in autism research(12, 20, 21, 31, 32). The most straightforward method to quantitatively assess prior integration is to test the effect of base rate probability on decision criterion. To date, only one study, Skewes and Gebauer (2016), using a categorical localization task of auditory stimuli, has directly addressed this in autism. They showed that autistic individuals adjusted their criterion to a lesser extent compared to non-autistics to favor the location category with the higher base rate probability. Notably, their study lacked explicit instruction regarding base rate manipulation or an independent test of it, leaving it unclear whether group differences were due to altered integration or simply reduced prior learning. In our study, by using explicit base rate instruction and an independent measure of prior knowledge—the gambling questions—we ensured that prior knowledge was consistent across groups. Additionally, by varying stimulus contrast levels, we tested for prior integration across various levels of sensory uncertainty within the same individual. Our results reveal that, after controlling for possible group differences in perceptual sensitivity and task knowledge, autistic individuals integrate priors to the same extent as non-autistic individuals. It has also been proposed that greater sensory precision in autism reduces the use of prior information(13–15). However, our findings do not support this proposal; if anything, we observed reduced sensitivity in the autistic group in some cases.

Expected Reward

Neuroimaging studies suggest that the reward system in autism might function differently compared to non-autistic individuals(33, 34). In our study, we tested the effect of expected monetary reward on decision criterion while independently verifying the manipulation of reward expectation. The results demonstrate that when both autistic and non-autistic groups were similar in their reward expectations, they similarly shifted their criterion to favor the more rewarded category. This finding suggests that in perceptual decision-making, the reward system in autistic individuals functions in a typical manner. Interestingly, both groups exhibited suboptimal decision biases to the same extent, contradicting claims of superior rational decision-making in autism(35).

Sensory uncertainty

The altered integration view suggests that enhanced sensory evidence, or lower sensory uncertainty, could be an alternative to the reduced priors account. For a Bayesian observer, reduced priors and lower sensory uncertainty are mathematically indistinguishable from decision outcomes alone(13). Lower sensory uncertainty does not necessarily entail higher performance but rather a subjective representation of reduced sensory uncertainty. To address the hypothesis that autistic individuals use information about their own sensory uncertainty in an atypical fashion, we employed an embedded category task to assess whether participants adjust their decision criterion based on sensory uncertainty per se. If autistic individuals have an atypical representation of sensory uncertainty, this would be reflected in their decision criterion. However, our results show a similar pattern of criterion adjustment in both groups, revealing that autistic individuals have a sensory uncertainty representation similar to non-autistic individuals.

Conclusions

In a series of three experiments, this study provides a systematic investigation of all Bayesian components of perceptual decision inference. The findings reveal that autistic individuals take into account prior knowledge, reward, and sensory uncertainty in a manner similar to non-autistic individuals, though both groups exhibit suboptimal behavior. These results challenge the current views of altered integration in perception and sensory processing in autism.

Thus, this study points to processes other than perceptual decision inference that may be altered in autism. For example, our findings showing an intact use of prior when they are explicitly given, and recent findings showing intact natural priors(36), suggest that the supposedly altered priors observed in autism might be specific to learned priors and related to the rate and flexibility of learning and updating(23, 37). Therefore, future research could focus on differences in perceptual prior learning and updating, or on implicit perceptual inferences that do not involve an explicit perceptual decision. Additionally, examining the role of attentional and working memory capacities may provide insights into how autistic individuals process sensory information.

The demonstration that autistic individuals are capable of typical integration of Bayesian components has important implications for developing more targeted interventions and support strategies aimed at enhancing perceptual and cognitive functioning in autistic individuals. Specifically, the findings show that given accurate and explicit knowledge, high-functioning autistic individuals can use contextual information and reward motivation in a typical manner. These findings have direct occupational implications.

Methods

Participants

A total of 52 adults diagnosed with autism (41 males and 11 females) and 93 non-autistic individuals (18 males and 75 females) participated in this study and received either monetary compensation (40 shekels/hour) or university credit compensation (3 credits/hour). Autistic participants were recruited from a reliable pool of participants routinely completing experiments for the Department of Special Education, in Dr. Hadad's lab. The two groups matched in age ($t(105) = .55$, $p = .59$), the mean age was $m = 26.70$ years old, $se = 0.86$, for the autistic group, and $m = 27.30$, $se = 0.64$, for the non-autistic group. The IQ was evaluated using the Test of Non-Verbal Intelligence (TONI-4) measuring cognitive functioning without the interference of language deficits(38). The two groups matched in IQ ($t(60.3) = .90$, $p = .37$), with a mean of $m = 99.3$, $se = 11.40$ for the autistic group, and $m = 101.0$, $se = 9.72$ for the non-autistic group. We used the Autistic Quotient (AQ) questionnaire to evaluate the participants' autistic traits, and a t-test ($t(64.9) = 6.97$, $p < .001$) revealed that the autistic group had a significantly higher AQ, $m = 27.0$, $se = 8.11$, compared to the non-autistic group, $m = 16.7$ $se = 6.69$. We maintained a minimum 24 hour-interval between consecutive experiments for each individual.

The autism diagnosis was confirmed through rigorous criteria, including the DSM-V, the Autism Diagnostic Interview (i.e., ADI-R52), and the Autism Diagnostic Observation Schedule (i.e., ASDOS-2). Moreover, all participants completed the Community Assessment of Psychic Experiences (i.e., CAPE) and AQ questionnaires, in their preferred language (Hebrew or English), either following the experimental phase or before the experiment, during the clinical assessment phase. We excluded non-autistic individuals with a history of epilepsy, neurological, psychiatric, or learning disorders, as well as those currently using psychiatric medications. We excluded individuals diagnosed with autism who have known genetic disorders (e.g., Down syndrome).

All participants provided written informed consent and the three studies received ethical clearance from the Institutional Review Board at the University of Haifa under the reference number 046/20.

Apparatus and Stimuli

Apparatus. Stimuli were programmed in Matlab (The MathWorks, Inc., Natick, MA) with the Psychophysics Toolbox extensions, and were presented on a gamma-corrected 21-in CRT monitor (1280 × 960 resolution, 85-Hz refresh rate). Participants used the keyboard to respond.

Stimuli. **Fig. 1b** illustrates the stimuli, experimental procedures, and tasks, based on Qamar et al. (2013), Adler and Ma (2018) and Denison et al. (2018). All stimuli were presented against a gray background (50 cd/m2). Each trial began with fixation (a black circle 0.2° of visual angle in diameter) for 500 ms, followed by the stimulus display for a duration of 50 ms. The stimulus was a sinusoidal grating with a two-dimensional Gaussian spatial envelope (i.e., Gabor patch), with *sd* = 0.325°, 85% contrast, and spatial frequency of 3 cycles per degree, presented at the center of the screen. In each trial, the orientation of the grating was randomly drawn from one of two Gaussian distributions, corresponding to the two stimulus categories (**Fig. 1c**). Following stimulus offset, participants reported both their category choice (Category A or B) and their level of confidence using a 4-point scale. This confidence rating scale ranged from high-confidence Category A to high-confidence Category B. The confidence data will be the focus of a separate paper. To manipulate the sensory uncertainty, we varied the stimulus contrast, randomly across trials, across seven fixed values (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) in the three experiments. In Experiment

1 and 2, the sensory uncertainty manipulation was used to create different levels of sensory uncertainty, to evaluate the adjustment of integration of prior and reward information into the decision criterion. In Experiment 3, we directly investigated the direct effect of sensory uncertainty on the decision boundaries.

Categories. Our experimental design incorporated continuous orientation distributions for each choice category, a critical feature enabling the separation of the participant's sensory noise from their decision rule(30, 39). In Task 1, used in the prior and reward experiments (Experiment 1 and Experiment 2), stimulus orientations were drawn from Gaussian distributions with means of $m_A = 86°$and $m_B = 94°$ (tilts around vertical), both with standard deviations of $s_A = s_B = 5^\circ$ (**Fig. 1c**, Task 1). In Task 2, used in the sensory uncertainty experiments (Experiment 3), we adopted a design that allowed us to test how changes in sensory uncertainty influence perceptual decisions(28). Here, stimulus orientations were drawn from Gaussian distributions with identical means, $m_A = m_B = 0^\circ$ (horizontal), but differing standard deviations, $s_A = 3^\circ$ and $s_B = 12^\circ$ (**Fig. 1c**, Task 2). These category means and standard deviations were chosen to yield an optimal observer accuracy level of approximately 80%.

Manipulation of priors, rewards and likelihood. In Experiment 1, to manipulate priors, we varied the base rate of Category B (and conversely, Category A) across three blocks of trials. Two blocks had imbalanced base rates: one with a higher probability for Category A (B = 25% and A = 75%) and the other with a higher probability for Category B (B = 75% and A = 25%). The third block had balanced probabilities (B = 50% and A = 50%).

In Experiment 2, to manipulate reward, we varied the base rate of Category B (and conversely, Category A) across three blocks of trials. Two blocks had imbalanced base rates: one with a higher probability for Category A (B = 25% and A = 75%) and the other with a higher probability for Category B (B = 75% and A = 25%). The third block had balanced probabilities (B = 50% and A = 50%).

In Experiment 2, we manipulated reward by varying the number of points awarded for correct answers in each category across three blocks. Two blocks had imbalanced reward: one with a higher reward for Category A (B = 1 point and A = 3 points), and the other with higher reward for Category B (B = 3 points and A = 1 point). The third block had balanced reward (B = 2 points and A = 2 points).

In both experiments, the neutral block was always performed second. The order of the low and high blocks was counterbalanced between participants.

In all experiments, we manipulated likelihood by varying stimulus contrast across trials in an unpredictable order (see Stimulus section). In Experiment 3, we maintained balanced category base rates and balanced rewards across all trials.

Procedure and Design

Training: To ensure that all participants understood the task and manipulations, at the beginning of each experiment we conducted an extensive training phase on the categories and the confidence keys, then on the prior/reward information at the beginning of each block (see **Supplementary Methods**).

Manipulations verification: To ensure the comprehension of the main manipulations (i.e., base rate or reward), a "check question" was randomly introduced during the experiment. In Experiment 1, participants were asked to hypothetically gamble an amount of money on a category, ranging from 0 to 99 cents, on the chances of the next trial belonging to that category, and that the amount left would be automatically gambled on the other category. They were informed that their predictive performance would determine a monetary/credit bonus in addition to the original compensation. In Experiment 2, participants were queried about the number of points they would earn if the next trial belonged to a specific category and their responses proved correct. In Experiment 3, there was no explicit manipulation and, therefore, no need to verify understanding of the experimental manipulation, yet, to maintain consistency and motivation we used the question from Experiment 1.

In Experiments 1 and 2, participants completed 960 experimental trials over approximately 50 minutes. Preliminary data indicated that Experiment 3 was more susceptible to noise. Therefore, participants performed two separate sessions of 960 trials each, with a minimum 24-hour gap between them.

Data analyses

All analyses were performed on R version 4.2.2. Because confidence data was not the focus of the present study, we considered only the categorical response, collapsing across confidence keys.

Outlier removal

In all Experiments, participants with an accuracy below 0.6 at the three highest contrast levels and across blocks were excluded from all analyses. Additionally, in Experiment 3, participants showing extreme criterion shift (k > 100) or a sensitivity (σ > 100) were removed from all analyses. Participants demonstrating extreme deviation from an optimal observer (c_{error} > 50 or k_{error} > 35) were excluded from the optimality statistical analyses. Participants exhibiting an averaged reaction time that was three standard deviations away from their group's mean were excluded from the reaction time analyses (**Table 1**).

Experiments 1 and 2

To ensure that participants comprehended the explicit manipulation of category probabilities and rewards across blocks, they were periodically probed to 1) gamble an amount on a specific category for the upcoming trial, ranging from 1 to 99, or 2) choose from 1 to 4 the number of points they expected to receive if they correctly selected a specific category. For Experiment 1, we computed an average of the amount gambled on Category B within each block by including answers where the amount was gambled on Category B and the subtraction of 100 minus answers where the amount was gambled on Category A within each block. For Experiment 2, we calculated an average point value associated with Category B within each block by including the number of points associated with Category B, and 4 minus the points associated with Category A, when participants were asked about each category. We ran a mixed-design ANOVA with 2 factors: 1) group (non-autistic, autistic) and 2) block (high base rate/reward for B, neutral base rate/reward for B, low base rate/reward for B) on the two scores.

We investigated how the probability to report a category was influenced by the different manipulations. We conducted a mixed-design ANOVA with 3 factors: 1) group (non-autistic, autistic), 2) block (high base rate/reward for B, neutral base rate/reward for B, low base rate/reward for B), and 3) orientation (-14, -12, -10, -8, -6, -4, -2, 0, 2, 4, 6, 8, 10, 12, 14), on the probability to report category B.

We utilized the framework of standard signal detection theory (SDT) to estimate two measures in each block of trials(40): 1) sensitivity (*d'*), reflecting the ability to discriminate the two categories, and 2) response bias (*c*), indicating the decision criterion employed by participants. Subsequently, we conducted a mixed-design ANOVA with the following factors: 1) contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72), 2) block (1, 2, 3), and 3) group (non-autistic, autistic) on both *d'* and *c*.

To gain insight into how participants adapted to a change of prior/reward information, we computed the shift in *c* between blocks characterized by low and high prior/reward conditions, denoted as $\Delta_{\text{criterion}}$. We conducted a mixed-design ANOVA with two factors: 1) contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) and 2) group (non-autistic, autistic) on the $\Delta_{\text{criterion}}$.

To determine the degree to which participants' criterion adjustment in response to changes in prior/reward conditions matched an ideal observer, we calculated the optimal criterion shift c_{opt} based on the optimal bias beta, calculated for a range of *d'* values (Eq. 1). Beta was calculated from the (Eq. 2) base rate (α) and (Eq. 3) reward (*r*) conditions(40). The parameters α and *h* could have a value of α = .25 (low base rate) or α = .75 (high base rate), and *r* = .25 (low reward) or *r* = .75 (high reward).

$$c_{\text{opt}} = \frac{\log(\beta_{\text{opt}})}{d'} \qquad (1)$$

$$\beta_{\text{opt}} = \frac{(1-\alpha)}{\alpha} \qquad (2)$$

$$\beta_{\text{opt}} = \frac{(1-r)}{r} \qquad (3)$$

Participants' suboptimality c_{error} was estimated as the difference between a participant's actual *c* and the corresponding c_{opt} based on their *d'* value, for each stimulus contrast. We conducted a mixed-design ANOVA with two factors: 1) contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) and 2) group (non-autistic, autistic) on the c_{error}.

We employed the Pearson correlation coefficient (*r*) to investigate the relationships between individuals' deviation from an optimal observer (c_{error}) and the AQ (see **Supplementary**

Results 1-2, **Supplementary Figs. 1a-b**). Correlations were calculated for both groups across prior/reward blocks and contrast levels.

Participants' reaction time was investigated with a mixed-design ANOVA with 3 factors: 1) contrast level (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72), group (non-autistic, autistic) and prior/reward block (high, neutral, and low) on their reaction time averaged across trials. The results are described in the **Supplementary Results 1-2** and **Supplementary Figures 2a-d**.

Significant effects from the ANOVAs were further investigated using paired and unpaired t-tests as appropriate to elucidate the nature of the observed differences. Bonferroni corrections were applied to control for multiple comparisons.

In addition to mixed-design ANOVAs, we employed t-test Bayes analyses to assess the evidence for differences between the autistic and non-autistic groups in sensitivity (*d'*), decision criterion ($\Delta_{\text{criterion}}$), and suboptimality ($c_{\text{error}}$). Bayes factors (BF) were used to quantify the likelihood of the data occurring under assumptions of the alternative hypothesis (H1 = difference between the two groups) over the null hypothesis (H0 = no difference between the two groups). BF < 1 indicates that the data provide evidence in favor of H0. 1 < BF < 3 indicates weak evidence for H1. 3 < BF < 10 indicates moderate evidence for H1. BF > 10 indicates strong evidence for H1 (41).

Experiment 3

To investigate how the manipulation influence participants' behavior, we conducted a mixed-design ANOVA with 3 factors: 1) group (non-autistic, autistic), 2) contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72), and 3) orientation (-14, -12, -10, -8, -6, -4, -2, 0, 2, 4, 6, 8, 10, 12, 14), on the probability to report category B.

We used a modified SDT model to estimate sensitivity and decision boundaries for the embedded category task. In this task, the two category distributions have the same mean orientation of 0°, but different standard deviations, s_A = 3° and s_B = 12°. The observer's estimated orientation is subject to additional internal noise, which depends on their perceptual sensitivity, σ, at each contrast. The standard deviation for the internal measurement distribution of each category across trials, combining external and internal noise, is then as displayed in equation (4).

$$\sigma_{\mathrm{cat}} = \sqrt{{s_{\mathrm{cat}}}^2 + {\sigma_{\mathrm{sens}}}^2} \tag{4}$$

In the embedded category task, the observer sets decision boundaries k to distinguish between the narrow category A and the broad category B. For the purpose of model fitting, we assume these boundaries to be symmetrical around zero degrees and stable across trials (**Fig. 1d**, **Task 2**). Then the probability of reporting category A for a given stimulus category C_{cat} with orientation noise σ_{cat} is given by the area of the internal measurement distribution across trials that falls between the decision boundaries.

$$p(r_{\mathrm{A}}|C_{\mathrm{cat}}, \sigma_{\mathrm{cat}}) = \int_{-k}^{k} \mathcal{N}(0, \sigma_{\mathrm{cat}}) \tag{5}$$

The probability of reporting Category B for a given stimulus category is 1 minus that number.

We estimated σ_{sens} and k from the data at each contrast level using the proportions of the participant's category reports across trials, according to equation (5). To do so, we took advantage of the fact that participants have the same internal noise and set of decision boundaries across both categories, and the means and standard deviations of the stimulus distributions are known. We first used an optimization procedure (*fmincon* in MATLAB), with a lower boundary of 0 and no upper boundary, to estimate what value of σ_{sens} was most consistent with a single k across both categories, given the reports. We then calculated k using the fitted value of σ_{sens}. We confirmed that this procedure correctly recovered σ_{sens} and k values from simulated data.

We conducted mixed-design ANOVAs on σ_{sens} and k with the following factors: 1) contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) and 2) group (non-autistic, autistic).

To control for any variation in perceptual sensitivity across participants, we calculated the optimal decision boundary k_{opt} using the participant's estimated σ_{sens} combined with the stimulus standard deviations to give σ_{A} and σ_{B} (Eq. 6),

$$k_{\text{opt}} = \pm \frac{\sigma_{\text{A}}^2 \sigma_{\text{B}}^2}{\sigma_{\text{B}}^2 - \sigma_{\text{A}}^2} \sqrt{2 \log \frac{\sigma_{\text{B}}}{\sigma_{\text{A}}}} \tag{6}$$

The optimal boundary k_{opt} lies at the crossing points of the internal measurement distributions for the two categories and maximizes performance across trials. We used the positive k values for all analyses.

We then estimated each participant's degree of suboptimality (k_{error}) by comparing k to the corresponding k_{opt} for each contrast level. We performed a mixed-design ANOVA with two factors: 1) contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) and 2) group (non-autistic, autistic) on the k_{error}.

Bayes factor, correlations, and reaction time analyses were conducted the same way as for Experiments 1 and 2. (see **Supplementary Results 3, Fig. 1c**, and **Fig. 2e** for the correlation and reaction time results).

Significant effects from the ANOVAs were further investigated using paired and unpaired t-tests as appropriate to elucidate the nature of the observed differences. Bonferroni corrections were applied to control for multiple comparisons.

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References

1. American Psychiatric Association, *Diagnostic and statistical manual of mental disorders: DSM-5.*, 5th edition (American Psychiatric Association, 2022).

2. C. E. Robertson, S. Baron-Cohen, Sensory perception in autism. *Nat. Rev. Neurosci.* **18**, 671–684 (2017).

3. B.-S. Hadad, A. Yashar, Sensory Perception in Autism: What Can We Learn?

4. T. Tavassoli, L. J. Miller, S. A. Schoen, D. M. Nielsen, S. Baron-Cohen, Sensory over-responsivity in adults with autism spectrum conditions. *Autism* **18**, 428–432 (2014).

5. L. Mottron, M. Dawson, I. Soulières, B. Hubert, J. Burack, Enhanced Perceptual Functioning in Autism: An Update, and Eight Principles of Autistic Perception. *J. Autism Dev. Disord.* **36**, 27–43 (2006).

6. H. Brown, R. A. Adams, I. Parees, M. Edwards, K. Friston, Active inference, sensory attenuation and illusions. *Cogn. Process.* **14**, 411–427 (2013).

7. D. C. Knill, W. Richards, *Perception as Bayesian inference.*, Cambridge University Press. (1996).

8. P. Mamassian, M. Landy, L. T. Maloney, *Bayesian modelling of visual perception.* (2002).

9. K. Friston, A theory of cortical responses. *Philos. Trans. R. Soc. B Biol. Sci.* **360**, 815–836 (2005).

10. J. Hohwy, A. Roepstorff, K. Friston, Predictive coding explains binocular rivalry: An epistemological review. *Cognition* **108**, 687–701 (2008).

11. R. N. Denison, E. A. Piazza, M. A. Silver, Predictive Context Influences Perceptual Selection during Binocular Rivalry. *Front. Hum. Neurosci.* **5** (2011).

12. E. Pellicano, D. Burr, When the world becomes 'too real': a Bayesian explanation of autistic perception. *Trends Cogn. Sci.* **16**, 504–510 (2012).

13. J. Brock, Alternative Bayesian accounts of autistic perception: Comment on Pellicano and Burr. *Trends Cogn. Sci.* **16**, 573–574 (2012).

14. R. P. Lawson, G. Rees, K. J. Friston, An aberrant precision account of autism. *Front. Hum. Neurosci.* **8** (2014).

15. P. Karvelis, A. R. Seitz, S. M. Lawrie, P. Seriès, Autistic traits, but not schizotypy, predict increased weighting of sensory information in Bayesian visual integration. *eLife* **7**, e34115 (2018).

16. J. J. A. Van Boxtel, H. Lu, A predictive coding perspective on autism spectrum disorders. *Front. Psychol.* **4** (2013).

17. S. Van De Cruys, *et al.*, Precise minds in uncertain worlds: Predictive coding in autism. *Psychol. Rev.* **121**, 649–675 (2014).

18. L. Sapey-Triomphe, L. Timmermans, J. Wagemans, Priors Bias Perceptual Decisions in Autism, But Are Less Flexibly Adjusted to the Context. *Autism Res.* **14**, 1134–1146 (2021).

19. N. Angeletos Chrysaitis, P. Seriès, 10 years of Bayesian theories of autism:a comprehensive review. *Neurosci. Biobehav. Rev.* 105022 (2022). https://doi.org/10.1016/j.neubiorev.2022.105022.

20. J. C. Skewes, E.-M. Jegindø, L. Gebauer, Perceptual inference and autistic traits. *Autism* **19**, 301–307 (2015).

21. J. C. Skewes, L. Gebauer, Brief Report: Suboptimal Auditory Localization in Autism Spectrum Disorder: Support for the Bayesian Account of Sensory Symptoms. *J. Autism Dev. Disord.* **46**, 2539–2547 (2016).

22. A. Croydon, T. Karaminis, L. Neil, D. Burr, E. Pellicano, The light-from-above prior is intact in autistic children. *J. Exp. Child Psychol.* **161**, 113–125 (2017).

23. R. Twito, B. Hadad, S. Szpiro, Is she still angry? Intact learning but no updating of facial expressions priors in autism. *Autism Res.* **17**, 934–946 (2024).

24. L. Acerbi, D. M. Wolpert, S. Vijayakumar, Internal Representations of Temporal Statistics and Feedback Calibrate Motor-Sensory Interval Timing. *PLoS Comput. Biol.* **8**, e1002771 (2012).

25. A. A. Scott-Van Zeeland, M. Dapretto, D. G. Ghahremani, R. A. Poldrack, S. Y. Bookheimer, Reward processing in autism. *Autism Res.* n/a-n/a (2010). https://doi.org/10.1002/aur.122.

26. S. Delmonte, *et al.*, Social and monetary reward processing in autism spectrum disorders. *Mol. Autism* **3**, 7 (2012).

27. S. Bottini, Social reward processing in individuals with autism spectrum disorder: A systematic review of the social motivation hypothesis. *Res. Autism Spectr. Disord.* **45**, 9–26 (2018).

28. A. T. Qamar, *et al.*, Trial-to-trial, uncertainty-based adjustment of decision boundaries in visual categorization. *Proc. Natl. Acad. Sci.* **110**, 20332–20337 (2013).

29. W. T. Adler, W. J. Ma, Comparing Bayesian and non-Bayesian accounts of human confidence reports. *PLOS Comput. Biol.* **14**, e1006572 (2018).

30. R. N. Denison, W. T. Adler, M. Carrasco, W. J. Ma, Humans incorporate attention-dependent uncertainty into perceptual decisions and confidence. *Proc. Natl. Acad. Sci.* **115**, 11090–11095 (2018).

31. T. Karaminis, *et al.*, Central tendency effects in time interval reproduction in autism. *Sci. Rep.* **6**, 28570 (2016).

32. M. Król, M. Król, The World as We Know It and the World as It Is: Eye-movementPatterns Reveal Decreased Use of Prior Knowledge in IndividualsWith Autism. 1386–1398 (2019).

33. K. K. M. Stavropoulos, L. J. Carver, Reward anticipation and processing of social versus nonsocial stimuli in children with and without autism spectrum disorders. *J. Child Psychol. Psychiatry* **55**, 1398–1408 (2014).

34. J. A. Richey, *et al.*, Common and distinct neural features of social and non-social reward processing in autism and social anxiety disorder. *Soc. Cogn. Affect. Neurosci.* **9**, 367–377 (2014).

35. L. Rozenkrantz, A. M. D'Mello, J. D. E. Gabrieli, Enhanced rationality in autism spectrum disorder. *Trends Cogn. Sci.* **25**, 685–696 (2021).

36. Z. Ahmad, N. Karsh, T. Ganel, B.-S. Hadad, E. Freud, Visual illusions modulate perception and action in autism spectrum disorder. *J. Vis.* **22**, 3573 (2022).

37. R. Randeniya, I. Vilares, J. B. Mattingley, M. I. Garrido, Reduced Context Updating but Intact Visual Priors in Autism. *Comput. Psychiatry* **5**, 140 (2021).

38. M. Goldberg Edelson, S. M. Edelson, S. Jung, Assessing the Intelligence of Individuals with Autism: A Cross-Cultural Replication of the Usefulness of the TONI. *Focus Autism Dev. Disabil.* **13**, 221–227 (1998).

39. J. L. Lee, R. Denison, W. J. Ma, Challenging the fixed-criterion model of perceptual decision-making. *Neurosci. Conscious.* **2023**, niad010 (2023).

40. S. K. Lynn, L. F. Barrett, "Utilizing" Signal Detection Theory. *Psychol. Sci.* **25**, 1663–1673 (2014).

41. R. E. Kass, A. E. Raftery, Bayes Factors. *J. Am. Stat. Assoc.* **90**, 773–795 (1995).

Figures and Tables

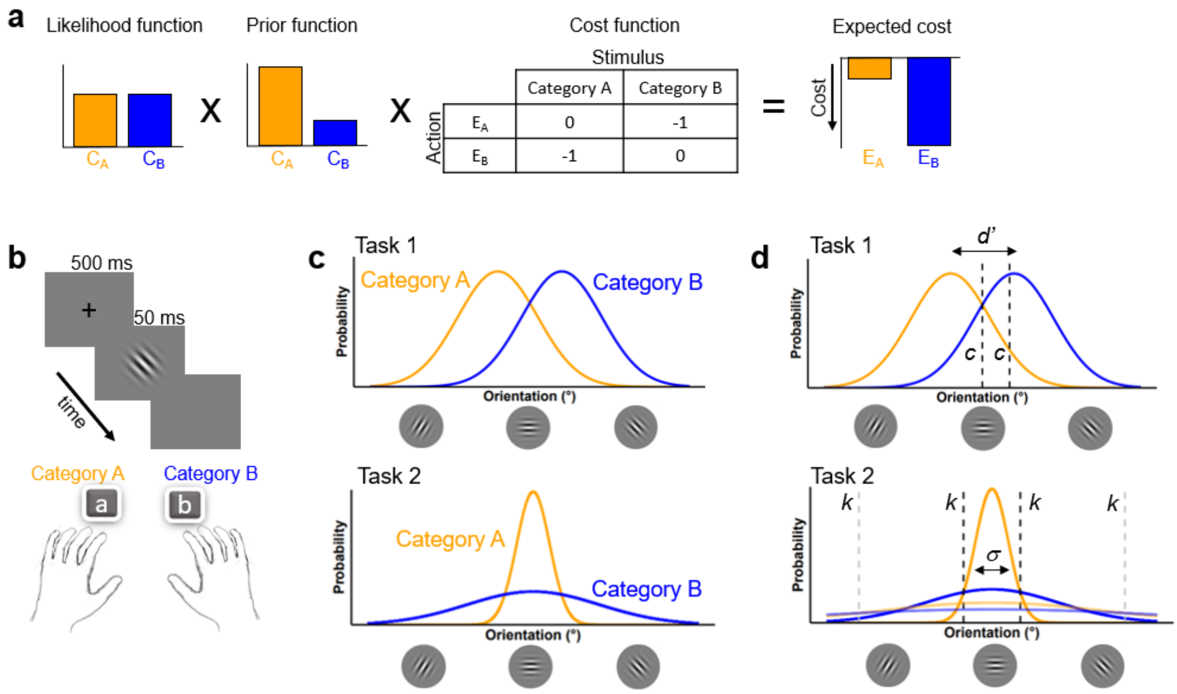


Fig. 1. Theoretical framework and tasks. (a) Graphical depiction of how the Bayesian inference predicts the internal response and optimal decision criterion during a categorization task. An observer is deciding between two possible categories (Category A or Category B). We obtain the expected cost of each decision (E_A and E_B) by multiplying the sensory uncertainty, prior, and cost corresponding to each stimulus and then summing the costs associated with the two possible categories. **(b)** Illustration of the sequence of events within a trial in all studies. **(c)** Stimulus orientation distributions for each category in Task 1 (Experiment 1 and Experiment 2) and Task 2 (Experiment 3). **(d)** Illustration of the internal representation of the category distributions. In Task 1 (top graphic), *d'* represents the sensitivity or ability to separate the two categories, and c represents the adjustment of the decision criterion when the prior favors Category A. In Task 2, (bottom graphic), the distributions with vivid colors represent the internal representations of the categories when the sensory noise is low, and the faded colors when the sensory noise is high. σ represents the internal noise, and *k* represents the decision boundaries, shifting outwards when the sensory noise is increasing.

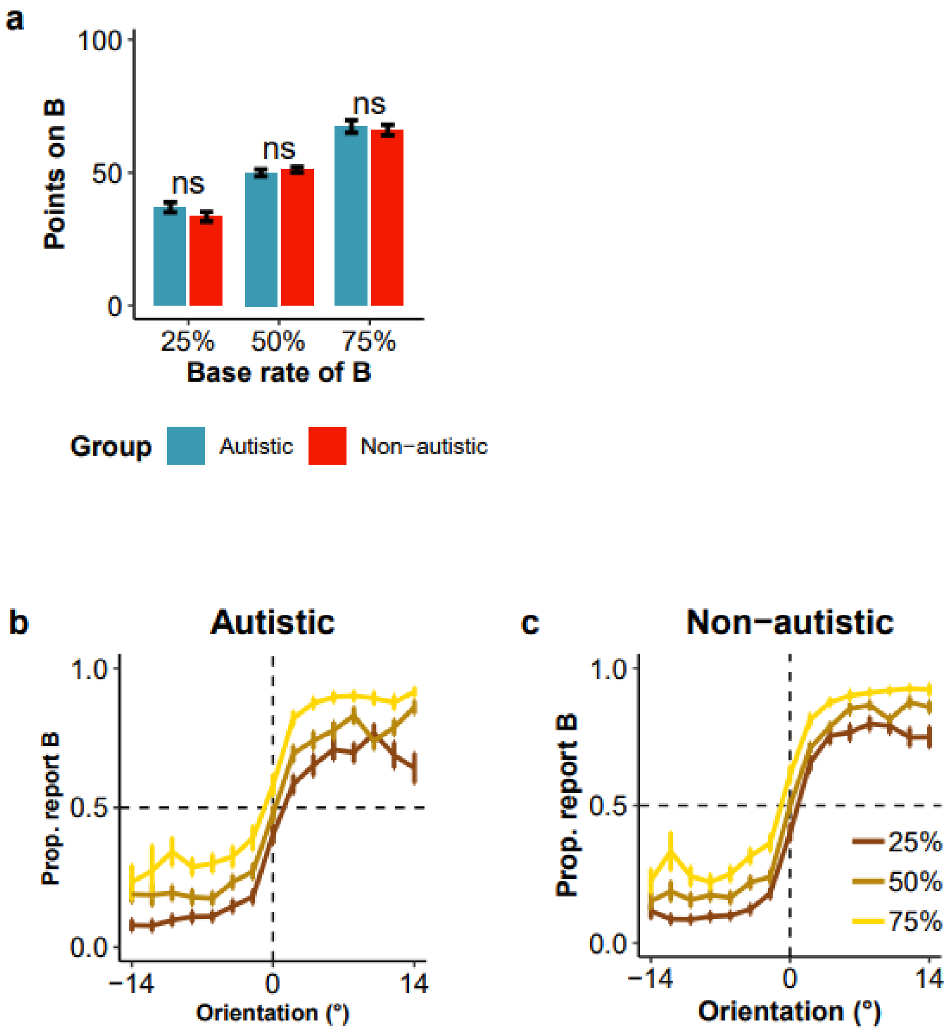


Fig 2. Task understanding and category report data for Experiment 1, prior manipulation. (a) Points gambled on category B as a function of base rate block. **(b, c)** Proportion of "Category B" responses as a function of orientation (x-axis) and Category B base rate block (line color) for the autistic and non-autistic groups. Data points show means across participants and error bars represent ±SE, per group of 30 autistic and 46 non-autistic participants in **(a)** and 31 autistic and 46 non-autistic participants in **(b, c)**. ns indicates no significant difference between groups evaluated using an unpaired t-test.

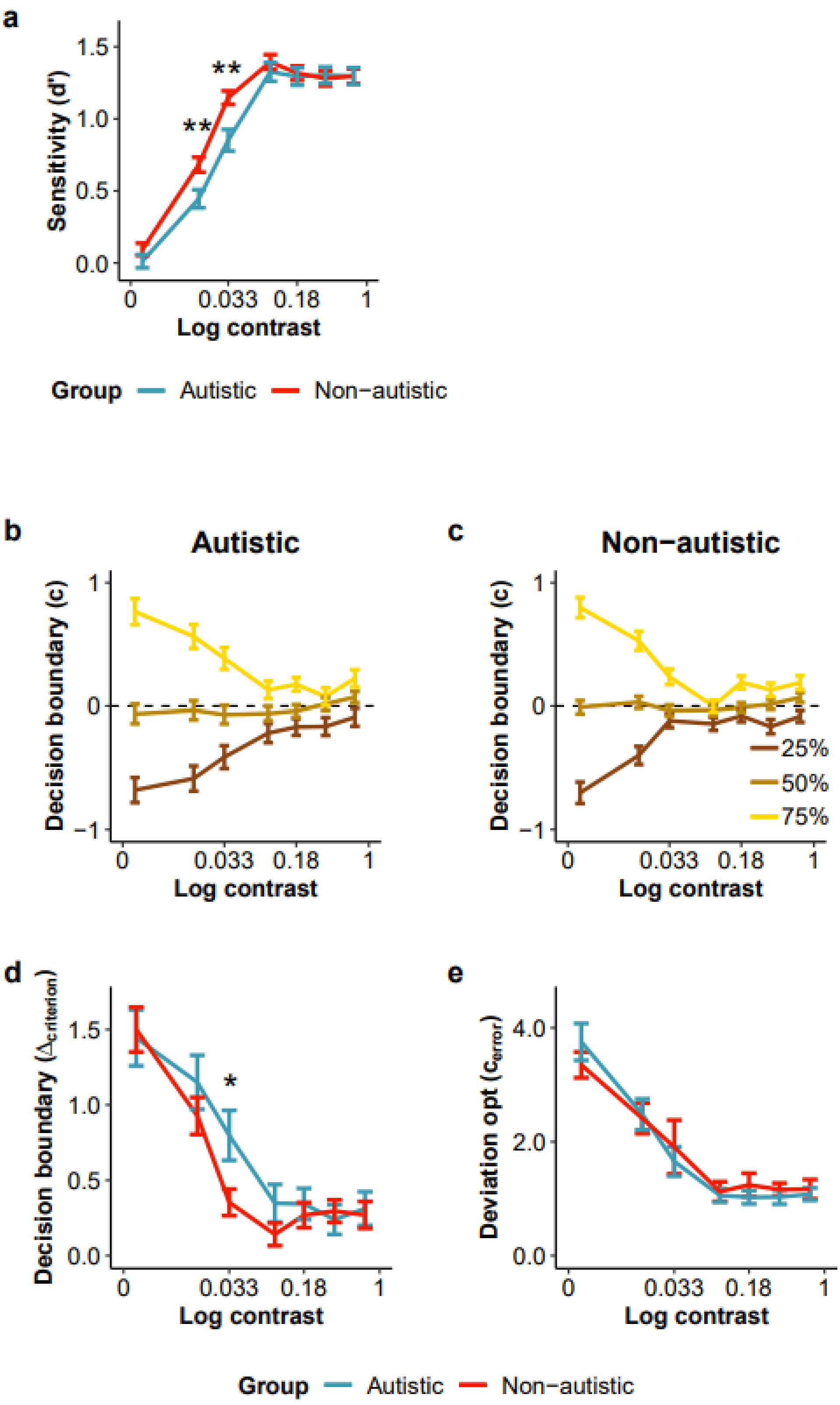


Fig. 3. Sensitivity, decision boundary, and optimal observer analyses for Experiment 1, prior manipulation. (a) Sensitivity (*d'*) for each group as a function of contrast and across base rates. Note that in all experiments, the relatively low sensitivity in both groups, even when contrast is high, is due to the limit of a maximum of 80% correct in these tasks. **(b, c)** Decision criterion (*c*) as a function of contrast for the three base

rate blocks for the autistic and non-autistic groups. The base rate legend gives the probability for category B to appear. **(d)** Difference between criterion shifts in biased (25% and 75%) base rate blocks ($\Delta_{criterion}$) for each group as a function of contrast on a log scale. **(e)** Deviation of criterion shift from optimality (c_{error}) as a function of contrast. Participants showed an increase in deviation from an optimal criteria adjustment as contrast decreased, with no difference between autistic and non-autistic groups in the degree to which the criterion was suboptimal. Data points show means across participants and error bars represent ±SE. The asterisks represent the group difference evaluated using unpaired t-tests, *$p \leq .05$, **$p \leq .01$. The sample size constituted 31 autistic and 46 non-autistic participants in **(a)**, **(b)**, **(c)** and **(d)**, and 30 autistic and 45 non-autistic participants in **(e)**.

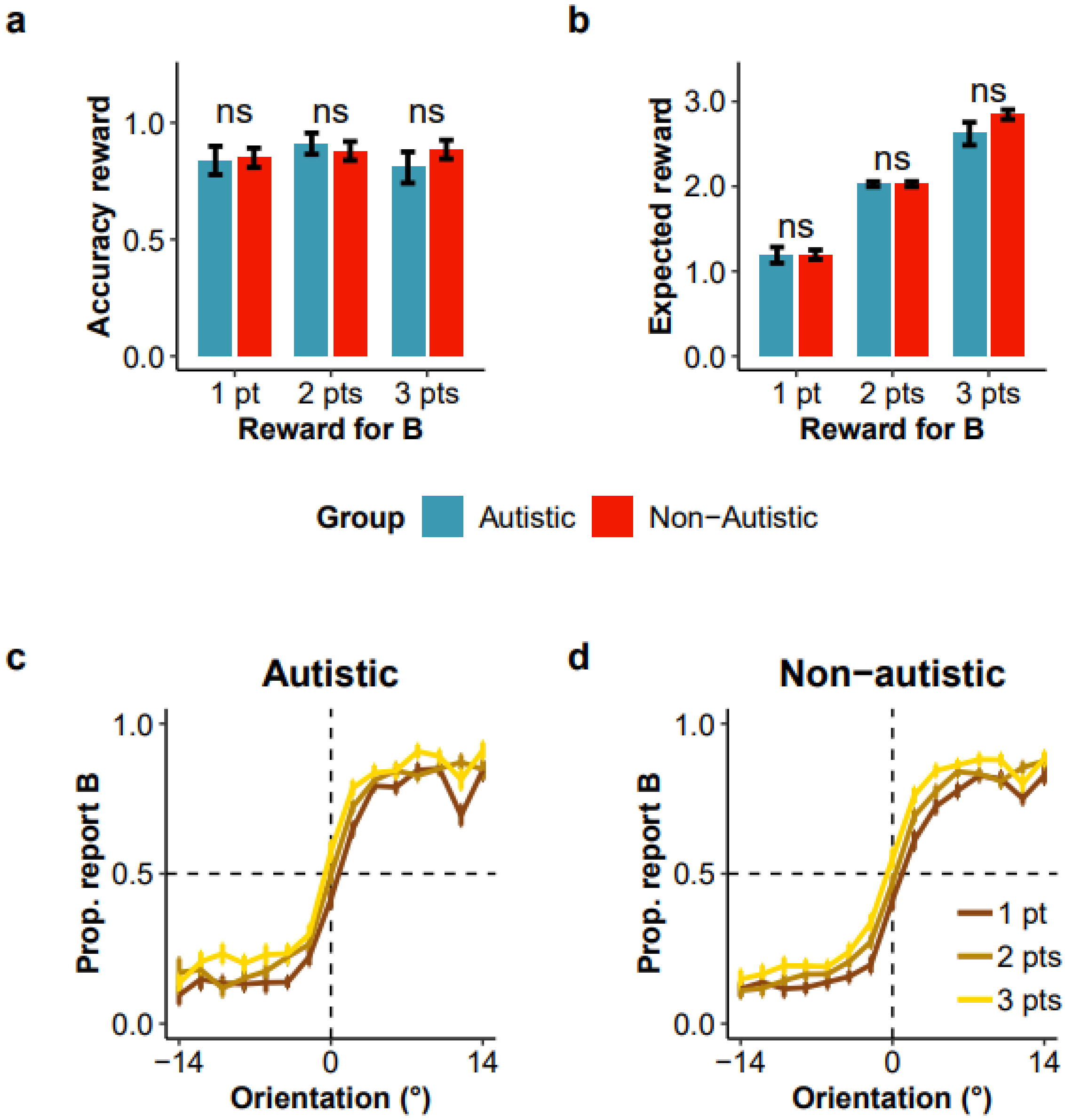


Fig. 4. Task understanding and category report data for Experiment 2, reward manipulation. (a) Accuracy for correctly associating point values with categories. **(b)** Number of points reported for correct categorizations of

Category B in each reward block. **(c, d)** Proportion of responses classified as “Category B” reported as a function of orientation (x-axis) and reward block (line color) for the autistic and non-autistic groups. The reward legend represents the number of points earned for correctly categorizing B. Data points show means across participants and error bars represent ±SE. The figures display the data averaged per group of 30 autistic and 44 non-autistic participants. ns indicates no significant difference between groups evaluated using unpaired t-tests.

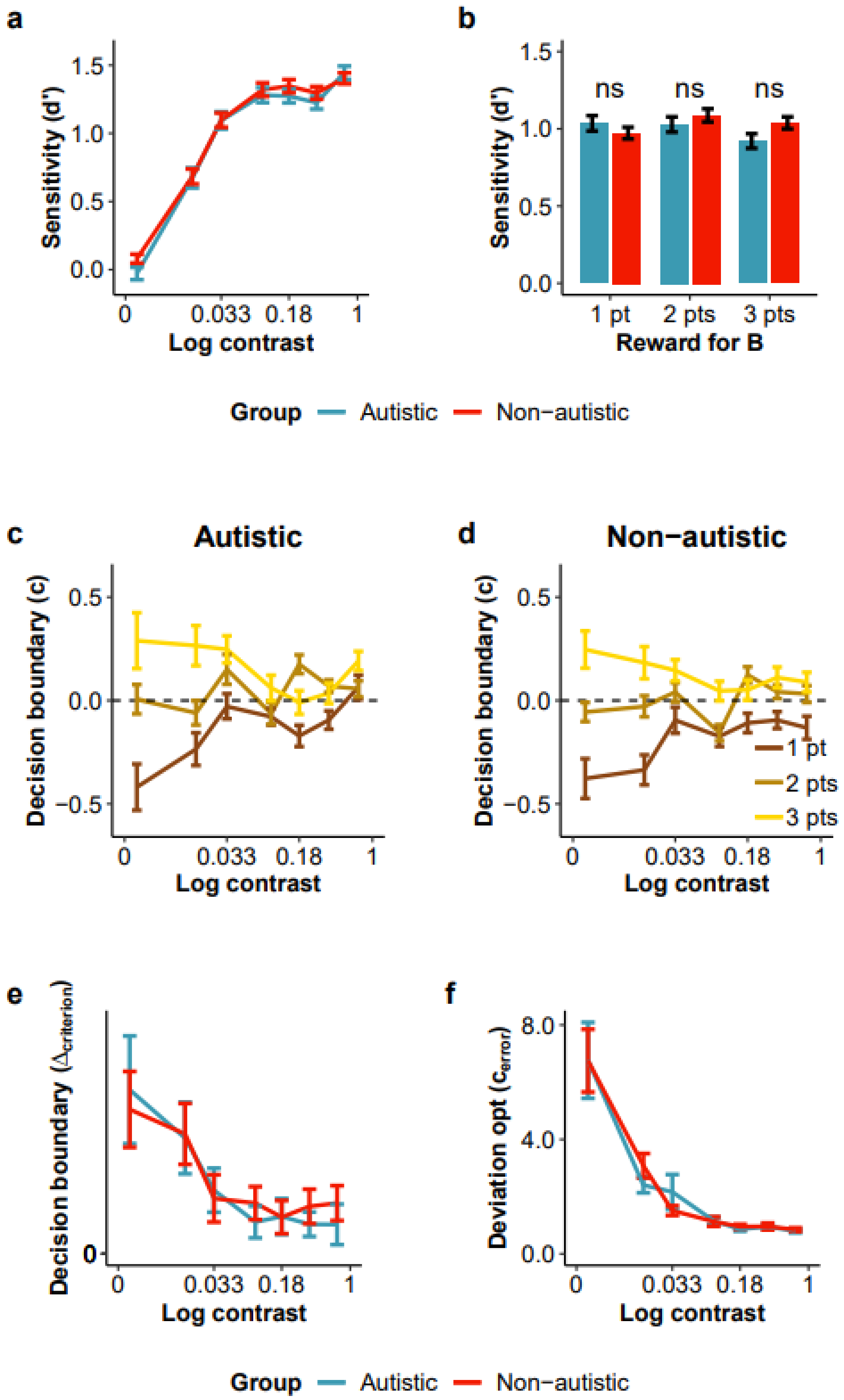


Fig. 5. Sensitivity, decision boundary, and optimal observer analyses for Experiment 2, reward manipulation. (a) Sensitivity (*d'*) of each group as a function of contrast. **(b)** Sensitivity d' as a function of reward for category B, illustrating the interaction between group and reward. **(c, d)** Decision criterion as a function of contrast represented on a log scale, and reward block for the autistic and non-autistic groups. **(e)** Decision

boundary shift $\Delta_{criterion}$ between reward blocks B = 1 point vs. 3 points, as a function of contrast. **(f)** Deviation from optimal criterion shift c_{error} as a function of contrast. Participants showed an increase in deviation from optimal criterion adjustment as contrast decreased. The reward legend shows the point reward for correctly categorizing B. Data points show means across participants and error bars represent ±SE. The sample size was 30 autistic and 44 non-autistic participants in **(a)**, **(b)**, **(c)**, **(d)**, and **(e),** and 30 autistic and 42 non-autistic participants in **(f)**. ns indicates no significant difference between groups evaluated using unpaired t-tests.

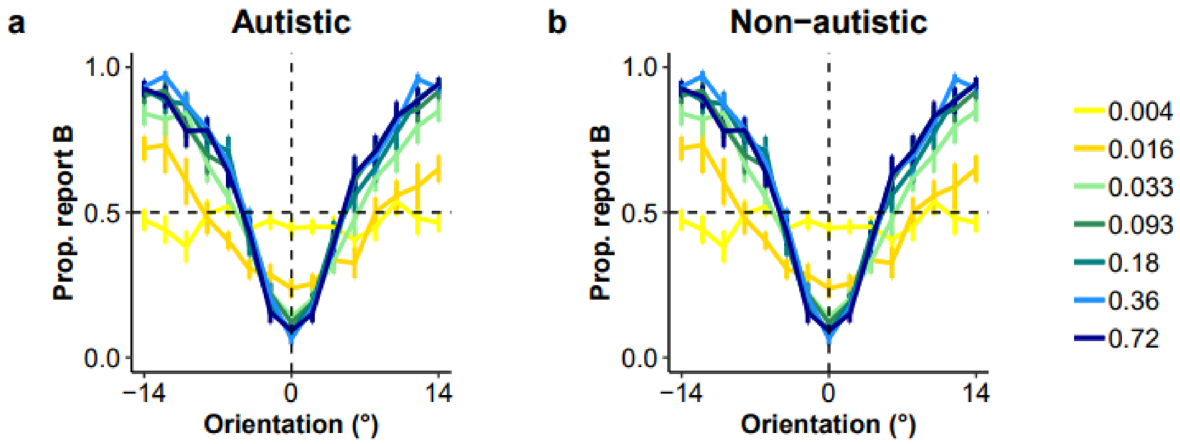


Fig. 6. Category report data for Experiment 3, sensory uncertainty manipulation. (A, B) Illustration of the proportion of reporting Category B as a function of orientation (x-axis) and contrast levels (line color) for the autistic (n = 27) and non-autistic (n = 40) groups. Data points show means across participants and error bars represent ±SE.

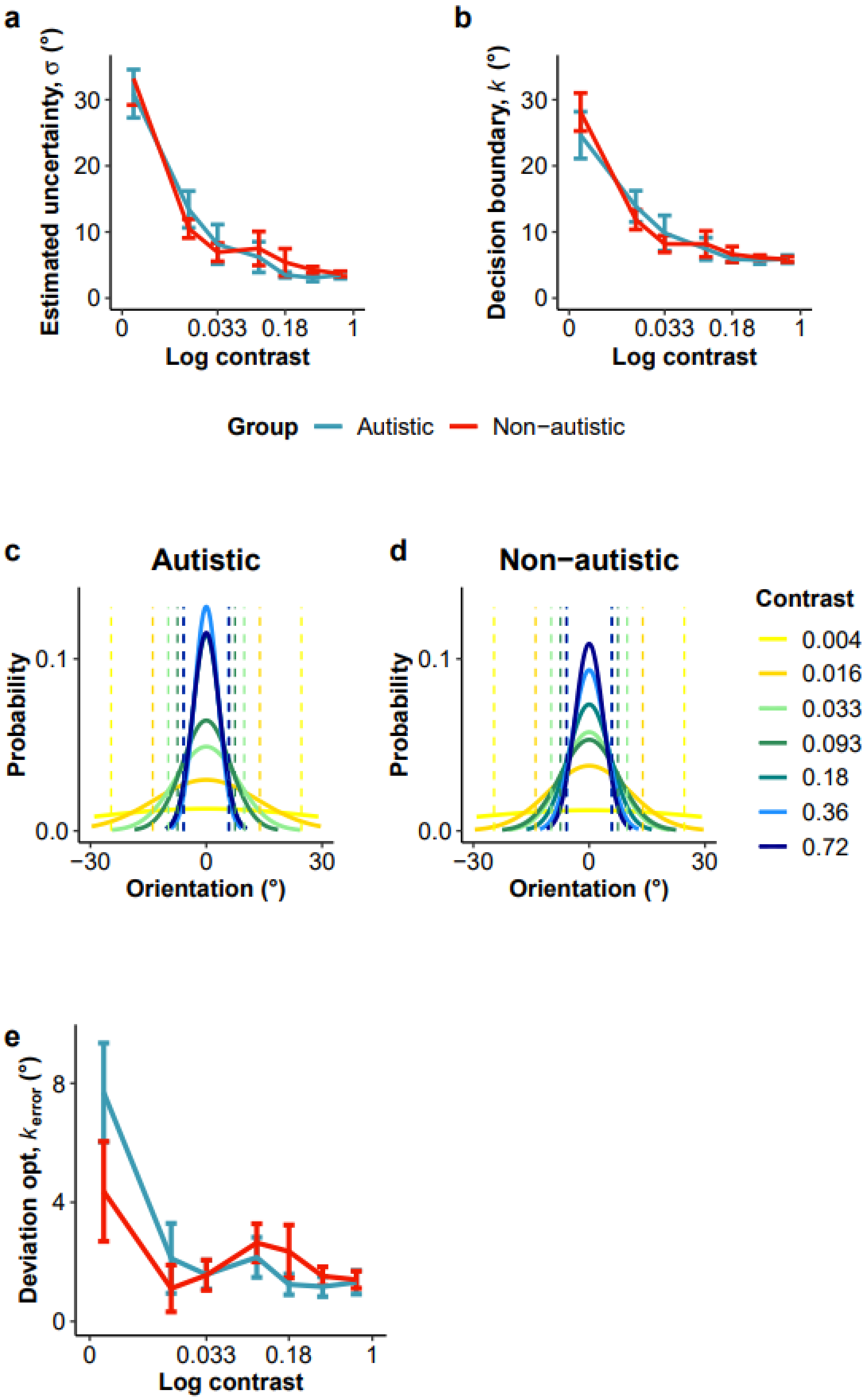

a
Estimated uncertainty, σ (°)
30
20
10
0
0
0.033
0.18
1
Log contrast
b
Decision boundary, k (°)
30
20
10
0
0
0.033
0.18
1
Log contrast
Group
Autistic
Non−autistic
c
Autistic
Probability
0.1
0.0
−30
0
30
Orientation (°)
d
Non−autistic
Probability
0.1
0.0
−30
0
30
Orientation (°)
Contrast
0.004
0.016
0.033
0.093
0.18
0.36
0.72
e
Deviation opt, k_{error} (°)
8
4
0
0
0.033
0.18
1
Log contrast

Fig. 7. Sensitivity, decision boundary, and optimal observer analyses for Experiment 3, sensory uncertainty manipulation. (a) Sensory uncertainty was evaluated by fitting the data with an SDT-style model adapted to the embedded category task. The fitted standard deviation, σ, provided an estimate of sensory uncertainty. A higher value indicates more sensory uncertainty compared to a lower value. **(b)** Category boundaries *k* were estimated from the same model and assumed to be symmetrical about zero degrees; the positive value is shown. **(c, d)** Probability of the category distributions for each level of contrast. The solid lines represent the precision of the distribution, with the sensory uncertainty (σ) as standard deviation of the category representations. The dashed lines represent the averaged decision boundaries (*k*) for each level of contrast **(e)** Deviation from optimality c_{error} as a function of contrast. Participants showed a larger deviation from the optimal decision boundaries as contrast decreased. Data points show means across participants and error bars represent ±SE. The sample size was 27 autistic and 40 non-autistic participants in **(a-d)**, and 27 autistic and 38 non-autistic participants in **(e)**.

	Overall n	Comprehension question	Sensitivity	Criteria	Optimality	rt	Correlation
Prior experiment	$n_{autistic} = 34$ $n_{non\text{-}autistic} = 49$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 46$	$n_{autistic} = 31$ $n_{non\text{-}autistic} = 46$	$n_{autistic} = 31$ $n_{non\text{-}autistic} = 46$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 45$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 45$	$n_{autistic} = 23$ $n_{non\text{-}autistic} = 40$
Reward experiment	$n_{autistic} = 32$ $n_{non\text{-}autistic} = 48$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 44$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 44$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 44$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 42$	$n_{autistic} = 30$ $n_{non\text{-}autistic} = 43$	$n_{autistic} = 27$ $n_{non\text{-}autistic} = 40$
Likelihood experiment	$n_{autistic} = 34$ $n_{non\text{-}autistic} = 44$		$n_{autistic} = 27$ $n_{non\text{-}autistic} = 40$	$n_{autistic} = 27$ $n_{non\text{-}autistic} = 40$	$n_{autistic} = 27$ $n_{non\text{-}autistic} = 38$	$n_{autistic} = 24$ $n_{non\text{-}autistic} = 39$	$n_{autistic} = 23$ $n_{non\text{-}autistic} = 37$

Table 1. Description of the sample sizes in the overall experiments, and in every statistical analysis, depending on the exclusion criteria based on participants' performances: comprehension question, sensitivity, criteria, deviation from an optimal observer, reaction time, and correlation between the AQ and the criterion shift.

Supplementary Information

Supplementary Methods

Category training. At the start of each experiment, participants were shown a printed graphic similar to **Figs. 1b-c**, which explained the generation of stimuli from specific distributions. Subsequently, to ensure participants were acquainted with the stimulus distributions, they underwent category training, first with each category separated, then with Category A and Category B combined with equal probabilities. In total, the practice consisted of 40 trials: 10 trials per category and 20 trials for the combined practice). On each trial, the stimulus orientation was drawn from the corresponding stimulus distribution (**Fig. 1c**). The stimulus presentation duration was 300 ms and contrast was 100%. Following the participant's response, a text message displaying their chosen category was presented, along with auditory correctness feedback (i.e., high pitch sound indicating a correct answer, and a low pitch sound indicating an incorrect answer).

Confidence training. Participants also completed a brief confidence training block to familiarize them with the key mappings used to report both their category choice and their confidence in each trial. We provided them with a printed graphic illustrating the key layout, indicating that participants needed to press one of eight buttons to indicate both category choice (A or B) and confidence level (on a 4-point scale). The confidence levels were labeled as "High," "Medium-High," "Medium-Low," and "Low." Trial-to-trial feedback consisted of a message confirming which category and confidence level they had reported, without any correctness feedback.

Base rate and reward training. In Experiment 1 and 2, we introduced the participants to the conditions of each experimental block (e.g., base rate for Experiment 1 and points for Experiment 2) with a verbal explanation followed by a practice session of 40 trials during which they reported both the category and their confidence level. Immediately after their response, the screen displayed the chosen category, along with a feedback sound. After reaching an accuracy of around 70%, reflecting that they were familiar enough with the categories, the response keys, and the block conditions, participants proceeded to complete the block of 280 test trials.

Throughout the experiment, participants did not receive trial-to-trial feedback to ensure that their decision boundaries were internally generated and not learned from correctness feedback. However, after every 50 trials, they were shown the percentage of trials they had correctly categorized to maintain motivation. In Experiments 2 and 3, participants were also provided with information on the points earned during the last 50 trials and the points accumulated over the experiment.

Supplementary Results 1: Prior manipulation

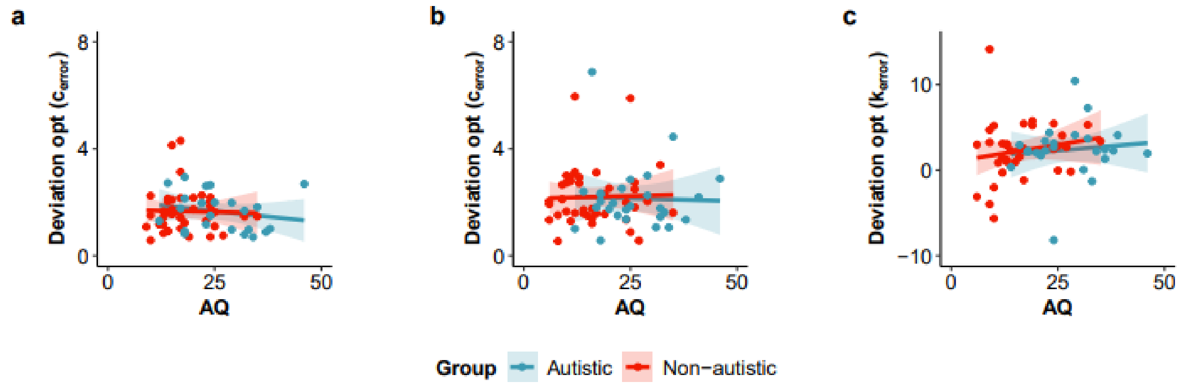
Perceptual sensitivity

The ANOVA analysis of the effects of base rate block, contrast and group on *d'* revealed a main effect of base rate, $F(2, 150) = 3.60$, $p = .030$, $\eta_p^2 = .05$, with greater sensitivity in the 50% base rate compared to the 25% base rate condition, $t(538) = 3.17$, $p = .005$). We also observed a significant interaction between base rate and contrast level ($F(12, 900) = 5.95$, $p < .001$, $\eta_p^2 = .07$).

Further analyses showed that the interaction is explained by a significant main effect of the base-rate in the contrast level 0.004 ($F(2, 152) = 3.50$, $p = .033$, $\eta_p^2 = .04$), 0.18 ($F(2, 152) = 7.83$, $p < .001$, $\eta_p^2 = .09$), 0.36 ($F(2, 152) = 7.12$, $p = .001$, $\eta_p^2 = .09$), and 0.72 ($F(2, 152) = 14.53$, $p < .001$, $\eta_p^2 = .16$), but not in the contrast level 0.016 ($F(2, 152) = 2.59$, $p = .078$, $\eta_p^2 = .03$), 0.033 ($F(2, 152) = 0.85$, $p = .429$, $\eta_p^2 < .01$) and 0.093 ($F(2, 152) = 1.71$, $p = 0.185$, $\eta_p^2 = .02$). In contrast level 0.004, the main effect of base-rate came from a significantly higher sensitivity in the base rate condition 25% compared to the condition 50% base ($t(151) = 2.77$, $p = .019$). In contrast level 0.18, the main effect of base rate was explained by a higher sensitivity in the base rate condition 50% compared to the condition 75% ($t(151) = 3.02$, $p = .009$). In the contrast level 0.36, the main effect of base-rate was explained by a lower sensitivity in the base rate condition 25% compared to the condition 75% ($t(143) = 2.61$, $p = .03$) and condition 50% ($t(150) = 2.83$, $p = .016$). Finally, in contrast level 0.72, the main effect of base rate was due to a significantly higher sensitivity in the base-rate condition 50% compared to the condition 75% ($t(152) = 4.53$, $p < .001$), and significantly higher sensitivity in the base-rate condition 50% compared to the condition 25% ($t(150) = 3.09$, $p = .002$).

Correlation between AQ and deviation from optimality

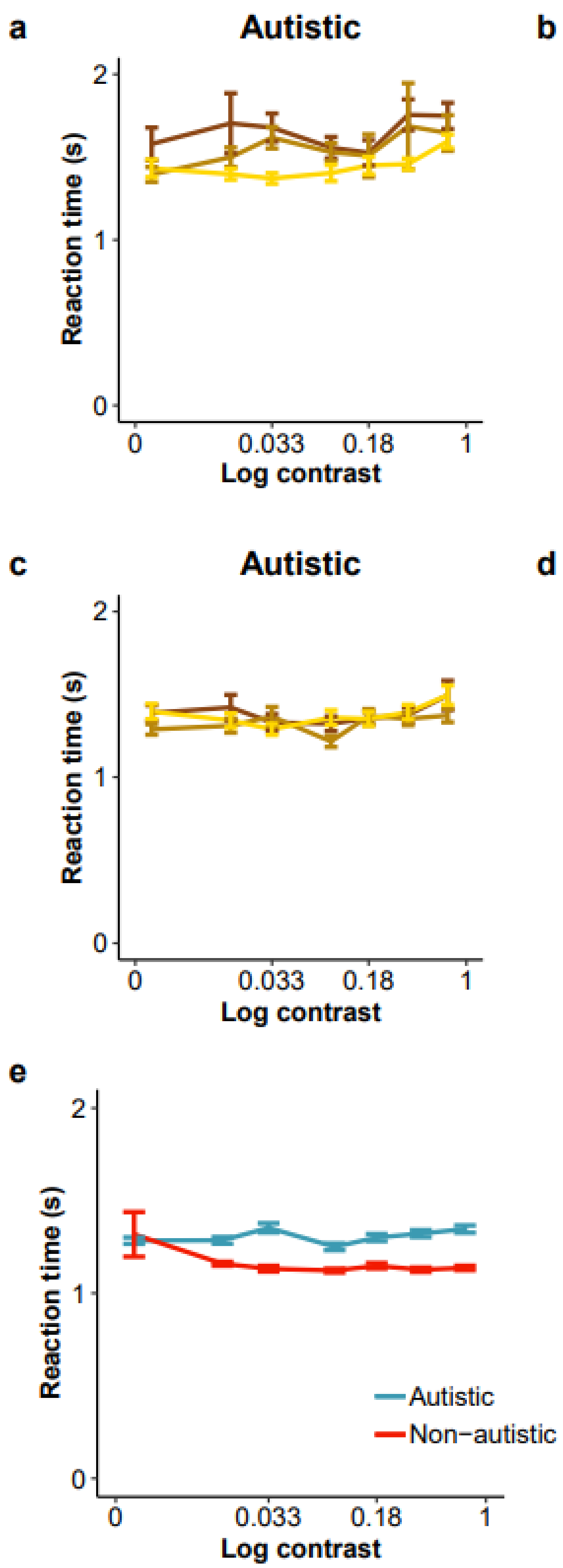
The correlation testing the relation between the AQ and c_{error} showed no significant relation between the two variables for either the autistic ($r(21) = -0.20$, $p = .36$) or the non-autistic ($r(38) = -0.03$, $p = .87$) group, as shown by the regression lines in **Supplementary Fig. 1a**. These results indicate that the level of autistic traits is not related to the way individuals integrate prior information while making perceptual decisions.



Supplementary Figure 1. Correlation between the deviation from optimality (c_{error}) and the Autistic Quotient (AQ). **(a)** Experiment 1, manipulating the prior. **(b)** Experiment 2, manipulating the reward. **(c)** Experiment 3, manipulating the sensory uncertainty. The data points represent individuals' suboptimality across contrast and block. The solid lines represent the linear regression line per group. The sample size constituted 23 autistic and 40 non-autistic participants in **(a)**, 27 autistic and 40 non-autistic participants in **(b)**, and 24 autistic and 37 non-autistic participants in **(c)**.

Reaction time

The ANOVA analyzing the effects of base rate block, group and contrast level on the averaged reaction time across trials revealed a main effect of group, $F(1, 73) = 11.47$, $p = .001$, $\eta_p^2 = 0.14$, with a significantly higher reaction time in the autistic compared to the non-autistic group, $t(943) = 8.90$, $p < .001$ (**Supplementary Fig. 2a**). The main effect of contrast level ($F(6, 438) = 1.08$, $p = .374$, $\eta_p^2 = .02$) and base rate block ($F(2, 146) = 1.80$, $p = .170$, $\eta_p^2 = .02$) were not significant. However, the interaction between contrast level and group was significant ($F(6, 438) = 2.35$, p = .030, $\eta_p^2 = .03$), and stemmed from a significantly higher reaction time in the autistic group in every contrast level except the level 0.004. The interaction between group and block ($F(2, 146) = 1.92$, $p = .150$, $\eta_p^2 = .03$), contrast level and base rate block ($F(12, 876) = 1.71$, $p = .300$, $\eta_p^2 = .02$), and the triple interaction between group, contrast level and base rate block ($F(12, 876) = 0.72$, $p = .730$, $\eta_p^2 = .01$) were not significant. The results are aligned with previous findings showing that autistic participants respond more slowly in a perceptual decision task than non-autistic participants[38]. Furthermore, the nonsignificant effect of contrast indicates that there was no tradeoff between speed and accuracy in both groups.



Supplementary Figure 2. Mean reaction time per group and contrast level for the experiments manipulating **(a, b)** base rate (Exp 1), **(c, d)** reward (Exp 2), and **(e)** sensory evidence (Exp 3). The base rate legend represents the probability for Category B to appear. The reward legend represents the reward attributed for correctly categorizing B. Data points show means across participants and error bars represent ±SE. The sample size constituted 30 autistic and 45 non-autistic participants in the prior experiment **(a, b)**, 30 autistic and 43 non-autistic participants in the reward experiment **(c, d)** and 24 autistic and 39 non-autistic participants in the sensory uncertainty experiment **(e)**.

Supplementary Results 2: Reward manipulation

Perceptual sensitivity

The ANOVA investigating the effects of reward block, contrast level, and group on the sensitivity (*d'*) revealed a significant interaction between reward block and contrast, $F(12, 864) = 3.56$ $p < .001$, $\eta_p^2 = .05$. The interaction stemmed from a main effect of reward block in the contrast level 0.033 ($F(2, 146) = 8.97$, $p < .001$, $\eta_p^2 = .11$), and 0.72 ($F(2, 146) = 6.20$, $p = .003$, $\eta_p^2 = .08$), but not in the contrast level 0.004 ($F(2, 146) = .14$, $p = .868$, $\eta_p^2 < .01$),0.016 ($F(2, 146) = .77$, $p = .47$, $\eta_p^2 < .01$), 0.093 ($F(2, 146) = 3.00$, $p = .053$, $\eta_p^2 = .04$), 0.18 ($F(2, 146) = 0.17$, $p = .842$, $\eta_p^2 < .01$), 0.36 ($F(2, 146) = 2.79$, $p = .065$, $\eta_p^2 = .04$). In contrast level 0.033, the sensitivity in the reward block "B = 2 points" was significantly higher than the reward blocks "B = 3 points" ($t(146) = 2.99$, $p = .01$) and "B = 1 point" ($t(144) = 2.88$, $p = .014$). As specified previously, Bonferroni corrections are applied to all t-tests investigating effects in within-subject conditions. In contrast level 0.72, the sensitivity was significantly higher in reward block "B = 2 points" compared to "B = 3 points" ($t(144) = 3.24$, $p = .005$). The ANOVA also revealed a significant three-way interaction between group, reward block, and contrast, $F(12, 864) = 2.29$, $p = .007$, $\eta_p^2 = .03$.The triple interaction stemmed from different interactions between reward and contrast level in the two groups. Indeed, we found a significant effect of reward block in the contrast level 0.033 ($F(2, 86) = 4.80$, $p = .011$, $\eta_p^2 = .10$), 0.18 ($F(2, 86) = 3.33$, $p = .040$, $\eta_p^2 = .07$), and 0.72 ($F(2, 86) = 6.86$, $p = .002$, $\eta_p^2 = .14$) for the non-autistic group, and a significant effect of reward block in the contrast levels 0.033 ($F(2, 58) = 5.50$, $p = .007$, $\eta_p^2 = .16$), 0.093 ($F(2, 58) = 5.93$, $p = .005$, $\eta_p^2 = .17$), and 0.18 ($F(2, 58) = 7.02$, $p = .002$, $\eta_p^2 = .20$) for the autistic group.

Correlation between AQ and deviation from optimality

The analysis of the relation between AQ and c_{error} demonstrated no significant correlations for either the autistic ($r(25) = -0.03$, $p = .88$) or non-autistic ($r(38) = 0.03$, $p = .86$) group (**Supplementary Fig. 1b**). These results support our previous finding by indicating that, just as for the autistic diagnosis, autistic traits are not moderating the way individuals incorporate reward information in their decision-making.

Reaction time

The mixed-design ANOVA investigating the effect of group, contrast level and block on the reaction time revealed a main effect of group ($F(1, 71) = 4.19$, $p = 0.044$, $\eta_p^2 = .06$, with the significantly greater reaction time in the autistic group ($t(979) = 6.65$, $p < .001$). The effect of contrast was also significant ($F(6, 426) = 2.83$, $p = 0.010$, $\eta_p^2 = 0.03$), and explained by a higher reaction time in the contrast level 0.72 compared to the contrast levels 0.033 $t(218) = 3.40$, $p = .017$) and 0.093 $t(218) = 3.86$, $p = .003$, and a higher reaction time in the contrast level 0.36 compared to the level 0.093 $t(218) = 3.13$, $p = .042$. The effect of reward block ($F(2, 142) = 1.47$, $p = 0.233$, $\eta_p^2 = 0.02$), the interactions between group and contrast level ($F(6, 426) = 1.21$, $p = 0.301$, $\eta_p^2 = 0.02$), between group and reward block ($F(2, 142) = 0.02$, $p = 0.98$, $\eta_p^2 < .01$), between contrast level and reward block ($F(12, 852) = 1.34$, $p = 0.19$, $\eta_p^2 = 0.02$), and the triple interaction between group, contrast level and reward block ($F(12, 852) = 1.14$, $p = 0.345$, $\eta_p^2 = 0.02$) were all not significant (**Supplementary Fig. 2b**). The results are consistent with Experiment 1 showing a slower reaction time for the autistic group. However, it seems that both groups exhibited a small tradeoff between speed and accuracy, indicated by a higher reaction time in higher contrast levels.

Supplementary Results 3: Sensory uncertainty manipulation

Correlation between AQ and deviation from optimality

The analysis of the correlation between AQ and c_{error} revealed no significant relation between the two variables for the autistic ($r(22) = 0.11$, $p = .62$) and the non-autistic ($r(35) = 0.12$, $p = .48$) groups (**Supplementary Fig. 1c**). These results, indicating that in both groups, the deviation from an optimal observer is not mediated by autistic traits, supported the findings that autistic individuals integrate the sensory uncertainty information in a typical manner.

Reaction time

The mixed-design ANOVA investigating the effect of group and contrast level on the reaction time revealed a main effect group ($F(1, 61) = 6.74$, $p = .012$, $\eta_p^2 = .10$) with a significantly higher reaction time in the autistic compared to the non-autistic group, $t(385) = 4.72$, $p < .001$ (**Supplementary Fig. 2c**). The effect of contrast ($F(6, 366) = 1.00$, $p = .428$, $\eta_p^2 = .02$), and the interaction between group and contrast $F(6, 366) = 1.92$, $p = .076$, $\eta_p^2 = .03$ were not significant. Once again, we replicated the higher reaction time for the autistic group, and as in Experiment 1, there was no tradeoff between speed and accuracy in Experiment 3.