Intact integration of reward information during perceptual decision-making in autism

Running title

Reward integration in autism

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Statements

Data availability statement

The data are deposited in the Open Science Framework repository and will be available after the publication of the article:
https://osf.io/mq4kn/?view_only=d9020f14b7d444358d008ff81ecbefe6

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Conflict of interest disclosure

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Ethics approval statement

This study received ethical approval from the Institutional Review Board at the University of Haifa, under reference number 046/20.

Lay summary

Sensitivity to reward is a key component that drives our day-to-day behavior. However, it has been suggested that this process is altered in autistic individuals, which could partially explain some social and communication symptoms. As an example, the lack of initiation of communication with peers could be explained by social interaction not being perceived as rewarding by autistic individuals. However, the hypothesis of reduced sensitivity to reward in autism is primarily based on neurobiological studies, and it remains unclear whether reward processing is broadly impaired, selectively impaired for social rewards, or not impaired at all. Here, we investigated whether autistic individuals integrate monetary reward information when making decisions based on perceptual stimuli. Specifically, autistic (n = 32) and non-autistic (n = 48) participants performed a categorization of orientation task, where monetary rewards given per correct answer varied across categories. Our results show that autistic individuals integrate reward information in a typical manner, challenging the hypothesis of general alteration of reward processing in autism.

Abstract

Alterations in reward processing were proposed as a contributing factor to social and communication symptoms in autism. However, the nature of these alterations remains unclear, and it is debated whether reduced sensitivity to reward is a general phenomenon, specific to social contexts, or exists at all. Evidence for reduced sensitivity to reward primarily comes from neurobiological studies, yet it remains uncertain how these findings translate to autistic behavior. A key challenge in addressing this question lies in assessing and comparing behavioral responses to reward between autistic and non-autistic groups. Here, we addressed this issue by investigating the integration of monetary reward information into behavior through the framework of Bayesian perceptual decision-making, enabling a quantitative evaluation of the direct contribution of reward to decision-making. Autistic (n = 32) and non-autistic (n = 48) participants performed an orientation categorization task, while the monetary reward given per correct answer varied across categories. Using signal-detection theory, we estimated decision boundaries while accounting for sensory uncertainty and prior expectation. Our results reveal that autistic individuals adjust their decision boundaries in response to monetary reward in a suboptimal but typical manner. These findings challenge the hypothesis of generalized alteration of reward processing in autism.

Keywords: reward, autism, Bayesian perception, decision-making, suboptimality

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

Introduction

Autism is characterized by a wide variety of phenotypes, ranging from low-level sensory processing to high-level theory of mind, alongside symptoms such as repetitive behaviors and restricted interests (American Psychiatric Association, 2022). Over the past decades, these symptoms have been associated with competing explanations. In the reward literature, they have been linked to atypical activation of neural networks involved in reward processing (Traynor & Hall, 2015), such as the striatum (Kohls et al., 2014, 2018; Langen et al., 2014), the dopamine circuit (Pavăl, 2017), and the anterior cingulate cortex (Thakkar et al., 2008). These findings support theories suggesting that atypical reward processing might partially explain the underlying core mechanisms of autism (Dichter & Adolphs, 2012; Kohls et al., 2012). However, whether atypical reward processing arises from a general reward integration deficit remains unclear. Moreover, in the perception line of research, autism symptoms have been associated with alterations in processes involved in sensory perception (reviewed in Hadad & Yashar, 2022; Heeger et al., 2017; Robertson & Baron-Cohen, 2017). Here, we used the perceptual decision-making domain to combine these lines of research to investigate whether and how reward processing during perceptual decision-making is altered in autism.

Several hypotheses regarding reward processing in autism have gained attention. The prominent social motivation hypothesis (Chevallier et al., 2012) suggests that social deficits in autism may stem from an atypically reduced tendency to experience social interactions as rewarding (Bhanji & Delgado, 2014). Other studies suggest that the reduced effect of social reward on behavior in autism may arise from a stronger motivation concerning personal, non-social interests (Kohls et al., 2018). Meanwhile, the general reward deficit hypothesis posits that reduced sensitivity to social reward stems from an overall diminished sensitivity to reward information—both social and non-social (Janouschek et al., 2021; Keifer et al., 2021).

In contrast to the general reward deficit view, the enhanced rationality theory (Rozenkrantz et al., 2021) predicts greater sensitivity to reward during monetary decision-making in autism. From this perspective, they are expected to integrate reward information more optimally than non-autistic individuals. However, no study to date has directly compared the integration of reward information during decision-making in autism to that of an optimal decision model observer.

Evidence for reduced response to reward mainly comes from fMRI studies. Specifically, a recent study revealed hypoactivation of the right ventral striatum in autism for both social and monetary rewards (Baumeister et al., 2023), suggesting a general atypical response to reward stimuli in autism. Behavioral investigations, however, have yielded mixed results. While some studies have reported atypical reward-related behavior in autism (Damiano et al., 2012; Mosner et al., 2017; Watson et al., 2015), other studies have shown no performance differences with either monetary or social reward stimuli (Pankert et al., 2014). Thus, whether and how autistic individuals are impacted by alterations in reward processing remains unknown.

A key challenge in addressing these questions lies in directly assessing and comparing behavioral responses to reward. Behavioral assessments of reward processing in autism have often relied on performance measures such as reaction time and accuracy (Matyjek et al., 2023; Neuhaus et al., 2015; Pankert et al., 2014), which may be influenced by other group differences, including sensory processing and decision criteria. Studies that have measured choice behaviour typically focus on overall choice preferences between rewarded and unrewarded stimuli (Dubey et al., 2017, 2022; Ruta et al., 2017), which may be insensitive to subtle differences in reward sensitivity.

Furthermore, the impact of reward can vary with task difficulty—for example, reward may have little effect if a task is too easy or difficult—and group differences in other task-related factors, such as sensory processing, can further modulate this interaction. However, no study has systematically compared the effect of reward on behavior between autistic and non-autistic individuals across varying levels of task performance.

The current study addresses this gap by quantitatively assessing the impact of monetary reward on choice behavior while controlling for sensory processing, task difficulty, and reward manipulation across groups. We used the framework of Bayesian perceptual decision-making, a formal decision model. According to Bayesian models, perception results from inference combining sensory evidence (i.e., likelihood) and internal models (i.e., priors) (Knill & Richards, 1996; Mamassian et al., 2002). The resulting posterior is then integrated with reward (cost function) to guide optimal behavior (or minimize expected cost, **Figs. 1a-b**) (Hanks et al., 2011; Huang et al., 2012; Rahnev & Denison, 2018). To illustrate this, consider the following scenario: you are walking in the street at night with your dog, and you see ahead an animal-like shadow. Whether you would decide to avoid this shadow depends on its shape (likelihood), your knowledge of whether cats are often running free in this area (prior), and whether your dog may strongly react to a cat (cost function).

Recently, Fazioli et al. (2025) revealed that, contrary to popular views (Brock, 2012; Friston, 2005; Karvelis et al., 2018; Król & Król, 2019; Pellicano & Burr, 2012), autistic individuals integrate prior knowledge and sensory evidence in a typical manner. However, it is still unknown whether autistic individuals integrate reward during perceptual decision-making in a manner comparable to non-autistic individuals. To account for potential group differences in sensory processing and decision criterion, we used Signal Detection Theory (SDT)—a specific case of Bayesian decision theory that separates sensitivity from decision criterion (Lynn & Barrett, 2014). This enabled us to quantify the impact of reward on decision criterion while controlling for sensory sensitivity.

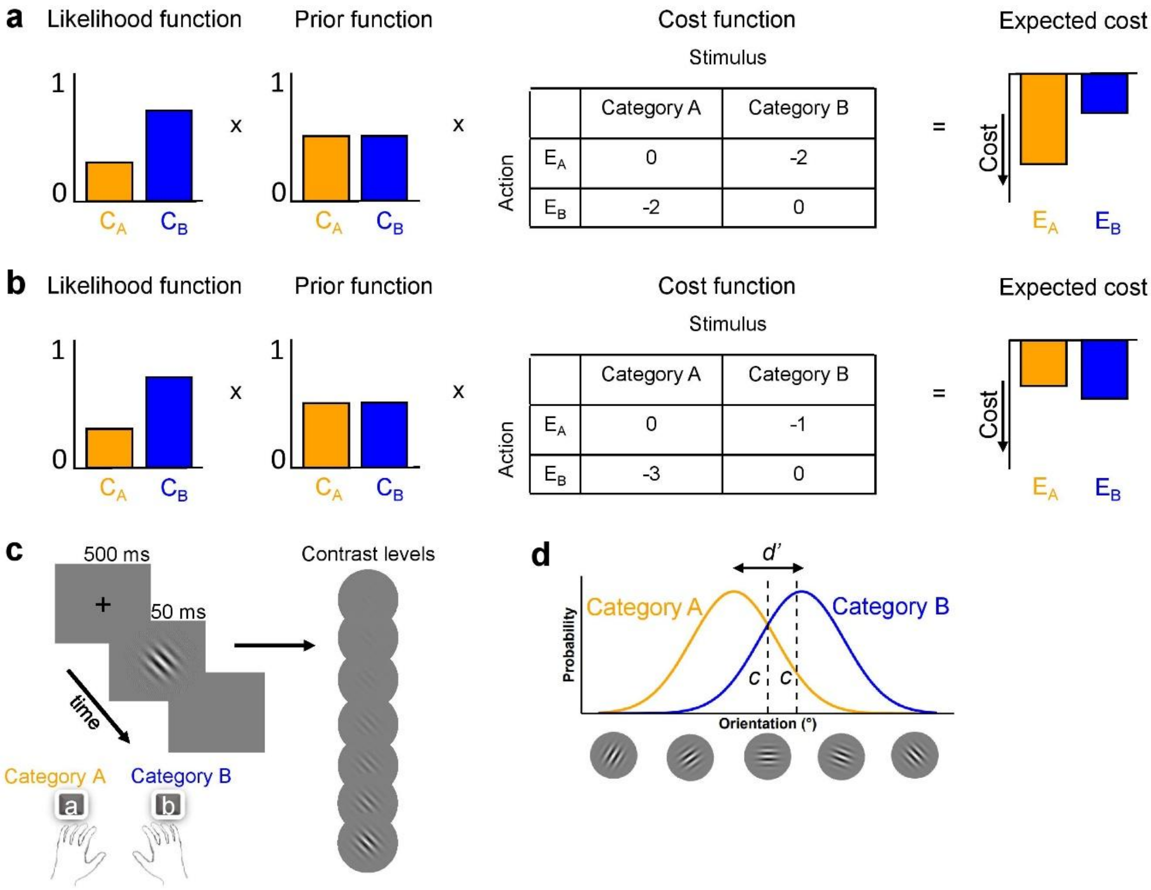

Fig. 1. Theoretical framework and task. (a) Graphical depiction of how the Bayesian inference predicts the internal response and optimal decision criterion during a categorization task. An observer is deciding between two possible categories (Category A or Category B). We obtain the expected cost of each decision (EA and EB) by multiplying the sensory uncertainty, prior, and cost corresponding to each stimulus and then summing the costs associated with the two possible categories. When more sensory evidence for Category B, equal priors, and a balanced reward system, the expected cost for choosing Category B is lower than Category A. **(b)** If the reward system favors Category A, the expected cost for choosing Category B is higher, despite higher sensory evidence for that category. **(c)** Illustration of the sequence of events within a trial, and the possible contrast levels. **(d)** Stimulus orientation distributions for the task and illustration of the internal representation of the category distributions. d' represents the sensitivity or ability to separate the two categories, and c represents the adjustment of the decision criterion when the reward favors Category A.

Autistic and non-autistic adults performed a categorization task (see **Fig. 1c**). To manipulate the cost function, we explicitly varied monetary reward between the two categories: in each block, one category could receive either more, the same, or less reward than the other. To measure the integration of reward information into the perceptual decision, we evaluated shifts in decision criteria in response to the change in reward. We also manipulated stimulus contrast, expecting participants to rely more on reward information (i.e., stronger criteria shift) when sensory evidence was lower (Rahnev & Denison, 2018). We aimed to evaluate whether autistic individuals shifted their criteria to the same or different extent as non-autistic individuals across the full range of perceptual sensitivity. According to the general reward deficit hypothesis, autistic individuals are expected to show smaller criterion shifts in response to reward compared to non-autistic individuals. In contrast, according to the enhanced rationality theory (Rozenkrantz et al., 2021) autistic individuals are expected to integrate reward information more optimally than non-autistic individuals, including a greater degree of integration as sensory evidence decreases.

Method

Participants

This study includes 32 adults diagnosed with autism (28 males and 4 females) and 48 non-autistic individuals (11 males and 37 females). Participants received a payment (40 shekels/hour) or course credits (3 credits/hour) as compensation. We assessed autistic traits in all participants using the Autistic Quotient (AQ) questionnaire. A t-test ($t(49.93) = 4.49$, $p < .001$) showed a significantly higher AQ for the autistic group compared to the non-autistic group. The groups were not significantly different in age ($t(67.96) = .30$, $p = .768$). We used the Test of Non-Verbal Intelligence (TONI-4) to measure the participants' Intellectual Quotient (IQ), independently from any language deficits (Goldberg Edelson et al., 1998). The two groups did not differ in IQ score ($t(46.47) = .15$, $p = .878$). The descriptive statistics of age, AQ, and IQ per group are displayed in **Table 1**.

Autistic participants were recruited from a trusted pool regularly involved in psychophysical testing at the university. The autism diagnosis was based on the DSM-V, the Autism Diagnostic Interview (i.e., ADI-R52), and the Autism Diagnostic Observation Schedule (i.e., ASDOS-2), and was confirmed in the laboratory using ADOS-2. All participants completed the Community Assessment of Psychic Experiences (i.e., CAPE) and AQ questionnaires in their preferred language, either following the experimental phase or during the clinical assessment.

Apparatus and Stimuli

The experimental design was based on Qamar et al. (2013), Adler & Ma (2018), and Denison et al. (2018), and strictly followed the procedure from Fazioli et al. (2025) as part of the same line of research on perceptual decision-making in autism.

Apparatus and stimuli. See Fazioli et al. (2025) for information about the generation of stimuli, monitor, and screen background. Each trial began with fixation (a black circle 0.2° of visual angle in diameter) for 500 ms, followed by the stimulus display for 50 ms (**Fig. 1c**). The stimulus was a sinusoidal grating with a two-dimensional Gaussian spatial envelope (i.e., Gabor patch), with $sd = 0.325°$, and spatial frequency of 3 cycles per degree, presented at the center of the screen. For every trial, the orientation of the grating was randomly drawn from one of two Gaussian distributions, corresponding to the two stimulus categories (**Fig. 1d**). Following stimulus offset, and without time limitation, observers simultaneously reported which category they thought the stimulus belonged to (Category A or B) and how confident they were about their choice. They answered using a 4-point confidence scale ranging from high-confidence Category A to high-confidence Category B. Using a single key press for both category choice and confidence prevents post-decision influences on the confidence judgment (Navajas et al., 2016). The confidence data will be presented in a separate paper. We manipulated sensory uncertainty to measure the adjustment of reward information integration into the decision criterion, using seven fixed values of contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) that randomly varied across trials (**Fig. 1c**).

Categories. Stimulus orientations were drawn from continuous Gaussian distributions for each category, enabling the separation of the observer's sensory noise from their decision rule (Denison et al., 2018; Lee et al., 2023). The distributions had means of m_A = 86°and m_B = 94° (tilts around horizontal), with standard deviation of $s_A = s_B = 5^{\circ}$ (**Fig. 1d**), creating an overlap between the two distributions. These parameters were chosen to yield an optimal observer accuracy level of approximately 80%.

Reward manipulation between blocks. Participants completed three blocks. We varied the number of points awarded for correct answers in each category across blocks, with low (B = 1 point and A = 3 points), neutral (B = 2 points and A = 2 points), and high (B = 3 points and A = 1 point) reward value for Category B compared to Category A. The neutral block was always performed second, and we counterbalanced the order of the low and high reward blocks between participants.

Procedure

Category training. At the beginning of the experiment, participants received instructions about the task, followed by explanations about the category distributions given with a printed graphic like **Fig. 1d**. To ensure participants understood the distributions, they completed a category training session of 40 trials with trial-to-trial correctness feedback, and where the stimuli were presented for 300 ms at 100% contrast.

Confidence training. Following the category training, participants received verbal instructions about the confidence rating, alongside a printed graphic illustrating the key layout. They were instructed to press one of eight keys to indicate both category choice (A or B) and confidence level (High, Medium-high, Medium-low, Low). Participants completed 40 practice trials to familiarize themselves with the key mapping. After each response, a message indicating the category and confidence choice was displayed, without correctness feedback.

See Fazioli et al., (2025) for details about all training.

Main experiment. We introduced participants to the reward manipulation block through a verbal explanation. They were instructed that the point system would change at the beginning of every block, that they were supposed to earn as many points as possible, and that the total amount of points would be converted to a monetary/credit bonus. At the beginning of each block, we specified the new point system, and they completed a practice session of 40 trials in which they reported only category choice. After each response, the screen displayed the chosen category and number of points earned in the trial, along with a feedback sound. We required that participants achieved a minimum of 70% accuracy before moving to the test session. Then, they completed the block of 280 test trials. To ensure participants relied on their decision boundaries rather than external feedback, no trial-to-trial feedback was provided throughout the experiment. However, to maintain motivation, after every 50 trials, participants received their categorization accuracy and information on the points earned during the last 50 trials and the points accumulated over the experiment. Participants completed 840 experimental trials over approximately 50 minutes.

Manipulation verification. To ensure the comprehension of the reward manipulations, a "check question" was randomly introduced during the experiment. Participants were asked about the number of points they would earn if the next trial belonged to a specific category, and their responses proved correct.

Data analyses

All analyses were performed on R version 4.2.2. Because the focus of the current article is on first-order decision-making only, we collapsed category responses across confidence keys.

Reward manipulation verification

To ensure that participants comprehended the explicit manipulation of rewards across blocks, they were periodically probed to choose from 1 to 4 the number of points they expected to receive if they correctly selected a specific category. 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. We ran a 2 x 3 mixed-design ANOVA: 1) group (non-autistic, autistic) as a between-subject factor, and 2) block (1: high reward for B, 2: neutral reward for B, 3: low reward for B) as a within-subject factor on the score.

Category reports

We investigated how reward manipulation influenced the probability of reporting a category across 16 levels of binned orientations. We conducted a 2 x 3 x 16 mixed-design ANOVA: 1) group (non-autistic, autistic), 2) block (1, 2, 3), and 3) orientation (-14, -12, -10, -8, -6, -4, -2, 0, 2, 4, 6, 8, 10, 12, 14) as a within-subject factor, on the probability to report category B.

Perceptual sensitivity and decision boundaries

We utilized the framework SDT (Lynn & Barrett, 2014) to estimate in each reward block, the sensitivity (*d'*), reflecting the ability to discriminate between the two categories, and the decision criterion (*c*), indicating the boundary employed by participants to favor one category over the other. Subsequently, we conducted a 7 x 3 x 2 mixed-design ANOVA: 1) contrast

(0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) as a within-subject factor, 2) block (1, 2, 3), and 3) group (non-autistic, autistic) on both *d’* and *c*.

Shift of decision boundaries

To evaluate how participants adapted to a change of reward information, we computed the difference in *c* between low and high reward condition blocks, such as $\Delta_{\text{criterion}} = c_{\text{B3 points}} - c_{\text{B1 point}}$. We conducted a 7 x 2 mixed-design ANOVA: 1) contrast (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72) and 2) group (non-autistic, autistic) on the $\Delta_{\text{criterion}}$.

Suboptimality

Criterion shifts should optimally adjust as a function of sensory uncertainty (the inverse of sensitivity), with a greater shift as sensory uncertainty increases. Therefore, to compare criterion adjustment in response to changes in reward conditions between groups, we needed to account for differences in sensitivity between and within participants. We used the ideal observer approach, where optimality represents the criterion shift that should be adopted for specific levels of *d'*.

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) (Lynn & Barrett, 2014). The parameter *r* could have a value of *r* = .25 (low reward) or *r* = .75 (high reward).

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

$$\beta_{\text{opt}} = \frac{(1-r)}{r} \tag{2}$$

$$c_{\text{error}} = c_{\text{opt}} - c \tag{3}$$

We estimated participants’ suboptimality c_{error} as the difference between a participant’s actual *c* and the corresponding c_{opt} based on their *d’* value, for each contrast level (Eq. 3). We conducted a 7 x 2 mixed-design ANOVA: 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}.

T-tests and Bayes Factors

We investigated significant effects identified in the ANOVAs by conducting paired and unpaired t-tests and applied Bonferroni corrections to account for multiple comparisons when appropriate. Effect sizes were calculated with partial eta squared.

In addition, we employed t-test Bayes analyses to assess the evidence for differences between the two groups in sensitivity (*d’*), decision criterion ($\Delta_{\text{criterion}}$), and suboptimality ($c_{\text{error}}$). We used the Bayes factors (BF) to quantify the likelihood of the data supporting the alternative hypothesis (H1 = difference between the two groups) compared to the null hypothesis (H0 = no difference between the two groups). BF < 1 indicates that the data provides evidence favoring H0. 1 < BF < 3 indicates weak evidence for H1. 3 < BF < 10 indicates moderate evidence for H1. BF > 10 indicates strong evidence for H1 (Kass & Raftery, 1995).

Additional analyses

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 Information** and **Supplementary Figure 1**). Correlations were calculated for both groups across reward blocks and contrast levels.

Participants' reaction time was investigated with a 7 x 2 x 3 mixed-design ANOVA: 1) contrast level (0.004, 0.016, 0.033, 0.093, 0.18, 0.36, 0.72), group (non-autistic, autistic) and reward block (high, neutral, and low) on averaged reaction time across trials. The results are described in the **Supplementary Information** and **Supplementary Figures 2a-b**.

Outlier removal

We excluded participants with an accuracy below 0.6 at the three highest contrast levels across blocks from all statistical analyses. Furthermore, we excluded participants demonstrating extreme deviation from an optimal observer ($c_{\text{error}} > 50$) from the optimality analyses, and participants exhibiting an average reaction time three standard deviations away from their group's mean from the reaction time analyses. We excluded participants who did not perform the AQ questionnaire from the correlation between AQ score and deviation from optimality analyses. The participant numbers included in every analysis are detailed in **Table 2**.

Results

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

Reward manipulation verification

First, we observed a very high accuracy in performing the expected 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. 2a**). Then, we conducted an ANOVA on the expected number of reward points reported by participants in response to the manipulation test questions. There was a significant effect of reward block on the expected reward for each category, $F(2, 144) = 198.02$, $p < .001$, $\eta_p^2 = .73$, while the main effect of group, $F(1, 72) = 3.39$, $p = .070$, $\eta_p^2 = .05$, and interaction between group and reward block were not significant, $F(2, 144) = 1.38$, $p = .254$, $\eta_p^2 = .02$ (**Fig. 2b**). These results confirm that both groups understood well and to the same extent the point values in the reward manipulation.

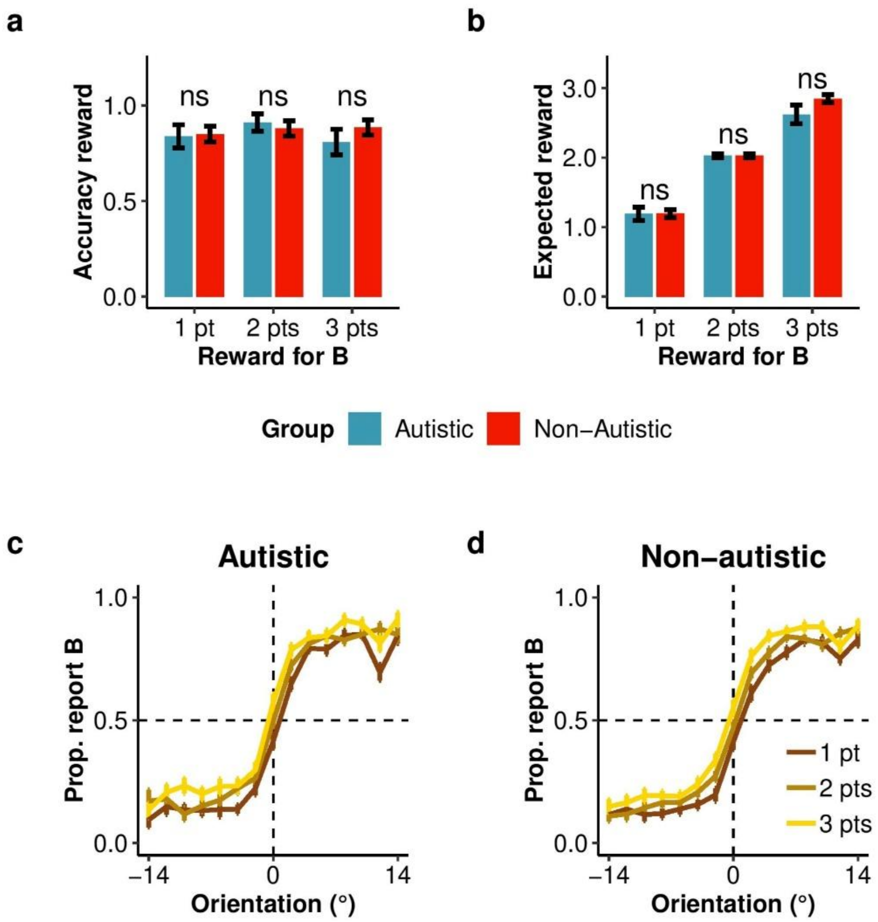

Fig. 2. Task understanding and category report data. **(a)** Accuracy for correctly associating point values with categories. **(b)** Number of points reported for correct categorizations of Category B in each reward block. **(c, d)** Proportion of responses classified as "Category B" reported as a function 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.

Categorization task

Category reports

The probability of reporting Category B increased as the stimulus was oriented more clockwise (toward positive values), as illustrated by the characteristic sigmoid shape in **Figs. 2c-d**. We observed an upward shift in the psychometric function when there was a higher reward for Category B, and a 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, $F(1.20, 86.35) = 21.59$, $p < .001$, $\eta_p^2 = .23$, with no difference between groups ($F(1, 72) = 1.30$, $p = .258$, $\eta_p^2 = .02$), nor interaction between group and block ($F(1.20, 86.35) = 0.04$, $p = .882$, $\eta_p^2 < .01$).

Perceptual sensitivity

Perceptual sensitivity to the category distributions increased with contrast, similarly for both groups. The ANOVA on *d'* revealed a significant effect of contrast level, $F(6, 432) = 184.19$, $p < .001$, $\eta_p^2 = .72$ (**Fig. 3a**). The main effect of group ($F(1, 72) = .39$, $p = .534$, $\eta_p^2 < .01$), and the interaction between group and contrast ($F(6, 432) = .48$, $p = .824$, $\eta_p^2 < .01$) were not significant, indicating that the two groups exhibited a comparable increase in sensitivity as contrast increased (**Fig. 3a**). The effect of reward block was not significant ($F(2, 144) = 2.46$, $p = .089$, $\eta_p^2 = .03$); however, the interaction between group and reward block was significant, $F(2, 144) = 3.29$, $p = .040$, $\eta_p^2 = .04$, and arises from the autistic vs. non-autistic group showing slightly higher sensitivity in the blocks "B = 1 point", $t(72) = 0.88$, $p = .381$, and " B = 2 point", $t(72) = 0.77$, $p = .442$, and a slightly lower sensitivity in the "B = 3 points" block, $t(72) = 1.64$, $p = .105$ (**Fig. 3b**). None of the group effects reached significance. 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 due to effects of reward block, which were significant at different levels of contrast between groups (see **Supplementary Information**). The Bayes factor assessing the likelihood of difference in *d'* between groups (H1) over no difference (H0) provided strong evidence supporting the null hypothesis ($BF_{10} = 0.10 \pm 0.22\%$). Overall, these results indicate that autistic participants show similar sensitivity to non-autistic participants.

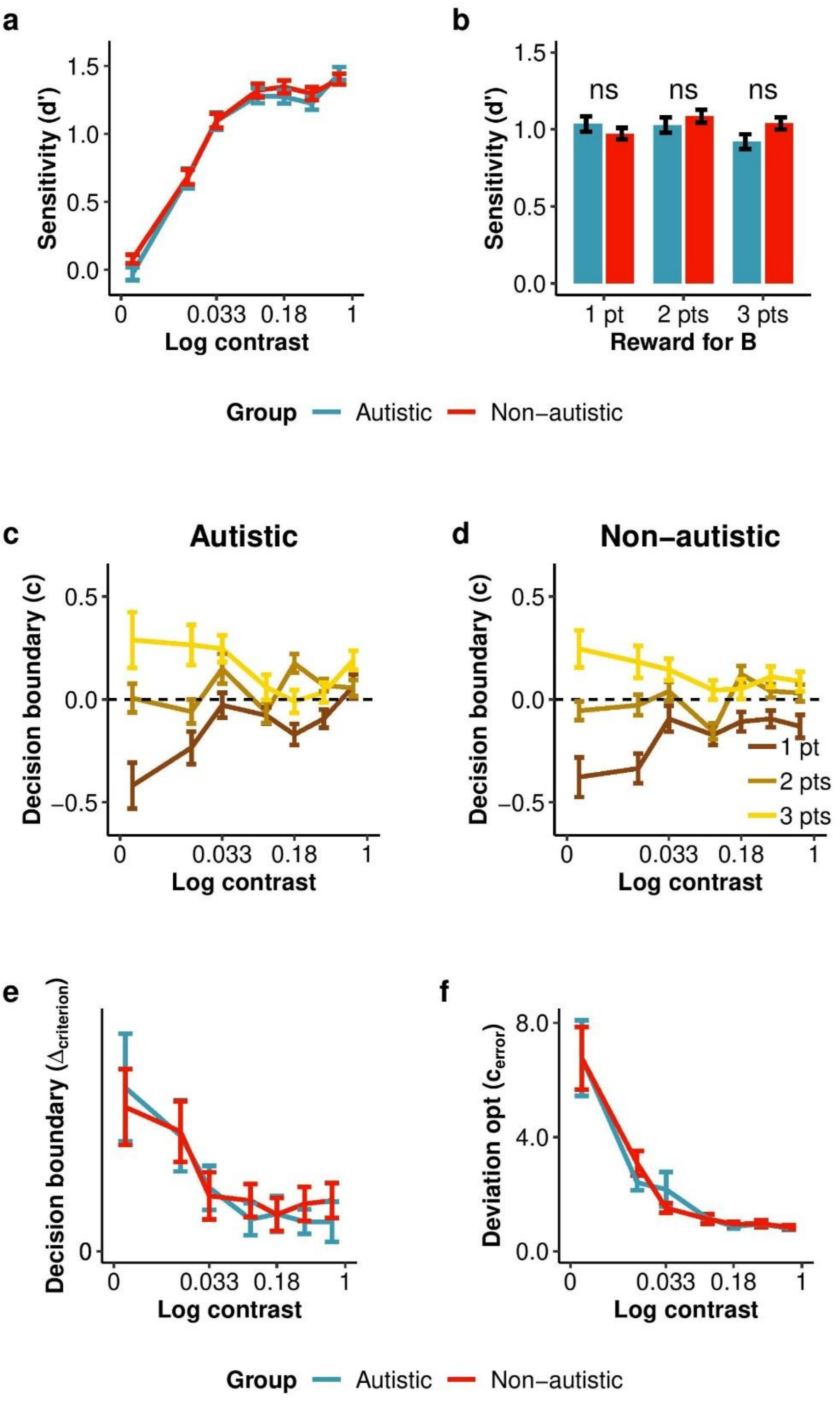

Fig. 3. Sensitivity, decision boundary, and optimal observer. **(a)** Sensitivity (d') of each group as a function of contrast. **(b)** Sensitivity d' as a function of reward for category B, illustrating the interaction between group and reward. **(c, d)** Decision criterion as a function of contrast represented on a log scale, and reward block for the autistic and non-autistic groups. **(e)** Decision boundary shift Δcriterion between reward blocks B = 1 point vs. 3 points, as a function of contrast. **(f)** Deviation from optimal criterion shift cerror as a function of contrast. 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.

Shift of decision boundaries

Decision boundaries reflected the reward manipulation, with an adjustment of criteria towards the most rewarding category in both groups (**Figs. 3c-d**). We quantified the effect of reward on decision criterion by computing the participants' criterion shift $\Delta_{\text{criterion}}$ between the two biased reward blocks (B = 1 point and B = 3 points) for each contrast level. 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. 3e**). 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 in criteria shift between groups. Autistic and non-autistic participants shifted their criteria to favor a more rewarding category, with a greater shift occurring when sensory evidence was weaker, consistent with the Bayesian predictions.

Suboptimality

To control any difference in sensitivity while assessing criterion shift, we computed the deviation from optimality (c_{error}) by calculating the difference between participants' criterion c and the optimal criterion c_{opt} for each level of contrast and the two unequal reward conditions. A c_{error} further from zero indicated a greater deviation from an optimal observer, with positive values indicating smaller-than-optimal shifts. 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 optimality as contrast decreased (**Fig. 3f**). 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 ($BF_{10} = 0.07 \pm 28\%$), provided evidence for H0 (i.e., no difference between groups in suboptimality), supporting the ANOVA.

Discussion

In this study, we investigated how autistic and non-autistic individuals integrate monetary reward information in perceptual decision-making, within the framework of Bayesian theory. Participants performed an orientation categorization task, in which we directly manipulated reward information, and measured how it affected decision criteria, including how shifts in criteria in response to reward depended on the strength of sensory evidence. The results demonstrate that, while controlling for the comprehension of the reward manipulation, autistic and non-autistic groups similarly shifted their criteria to favor the more rewarded category, with a greater shift occurring as sensory evidence decreased. Both groups showed suboptimal decision behavior by not shifting their criteria enough to maximize expected reward, and the degree of suboptimality increased with decreasing sensory evidence. These findings suggest that in perceptual decision-making, autistic individuals integrate reward information with sensory evidence in a typical, but suboptimal manner.

Many neural studies investigating reward processing in autism found atypical brain activations when processing social (Delmonte et al., 2012; Scott-Van Zeeland et al., 2010), or both social and monetary rewards (Baumeister et al., 2023; Dichter et al., 2012; Richey et al., 2014). However, these studies often failed to identify corresponding atypical behaviors, which were mainly measures of performance. Similarly, most behavioral studies assessed the effect of rewards on autism through overall performance (Damiano et al., 2012; Lin et al., 2012; Mosner et al., 2017; Pankert et al., 2014; Watson et al., 2015), which—being affected by other cognitive abilities—may not be sensitive enough to isolate reward processing. The present study addresses these limitations by directly and quantitatively assessing changes in decision boundaries in response to variations in reward while controlling for task difficulty and perceptual sensitivity. The results show adjustment in reward integration in response to sensory evidence in both groups, indicating that autistic and non-autistic individuals exhibit comparable effects of monetary reward. These findings suggest that reductions in fMRI responses to monetary reward in autism do not necessarily indicate behavioral differences in response to reward.

Discrepancies between behavioral findings— such as those presented in this article— showing intact integration of monetary reward in autism, and neural findings indicating atypical brain activity during monetary reward processing could be explained, first, by cognitive and behavioral compensatory mechanisms. These mechanisms may emerge over time to regulate autistic behavior towards reward, and could result in intact behavior even in the presence of altered neural activations. Rigorously testing reward processing across autistic development could clarify this hypothesis and provide deeper insights into the etiology of autism. Second, reduced neural activities in targeted areas may not necessarily reflect atypical reward processing, but could reflect overall reductions in stimulus-response activity, attention, or arousal. Third, reward integration during perceptual decision-making may rely on intact computations unrelated to the previously observed neural alterations. Therefore, there is a necessity to unify neural and behavioral frameworks and theories when investigating neurodevelopmental conditions.

The present study may seem inconsistent with the general reward deficit hypothesis. However, the reward information was explicit, and participants received extensive training on the point system to control for possible differences in reward learning. Therefore, the difference in findings in previous behavioral studies could stem from atypical reward learning (Lin et al., 2012), which emphasizes the need to distinguish the ability to learn from the ability to integrate rewards. Similarly, Fazioli et al. (2025) highlighted the importance of separating the process of learning from the process of integrating Bayesian components in decision tasks. Indeed, by manipulating prior information explicitly, and controlling for participant comprehension, they showed that autistic individuals integrated priors in a typical manner when making decisions on basic-feature stimuli. These results contradicted a dominant hypothesis of a general underuse of priors in autism. Together, Fazioli et al. (2025) and the current findings show that autistic individuals integrate explicit prior and reward information, as well as sensory evidence (see, Fazioli et al., 2025, Task 2) when making perceptual decisions on basic-feature stimuli, challenging the view of atypical Bayesian perception in autism. However, similarly to the prior processing in autism, whether the learning of implicit reward is atypical in autism remains an open question.

Furthermore, by comparing participants' criterion shift to an optimal observer's, we directly tested whether autistic individuals exhibit enhanced rationality when integrating reward information. This theory describes autistic behavior towards rewards as less biased by irrelevant information, such as the framing of the question (De Martino et al., 2008) and oriented towards choices that lead to more monetary gains (Jin et al., 2020; Mussey et al., 2015; Tei et al., 2018; Vella et al., 2018). However, our findings showed that autistic individuals exhibit the same suboptimality as their non-autistic counterparts, by under-shifting their decision criterion when sensory evidence decreased. These results contradict the enhanced rationality theory regarding decisions based on low-level stimuli and monetary reward. Further investigations should be conducted to directly test the optimality of the reward integration when decisions involve more complex sources of information (e.g., irrelevant information, social reward).

The fact that autistic individuals adjust decision behavior in response to reward as effectively as non-autistic individuals has both clinical and occupational implications. It suggests that, at least when using explicit instruction regarding reward, reward-based intervention and training may have the same effectiveness in the autistic population. Note though, that these findings apply to monetary reward but not to social reward, and it is still unclear whether autistic individuals have reduced behavioral responses to social reward. The current study demonstrates that perceptual decision-making and Bayesian inference can effectively detect subtle variations in monetary reward processing. Future research should use this approach to investigate social and implicit reward processing in non-autistic and autistic populations. Indeed, these two types of reward are more challenging than explicit monetary reward, especially in real-life scenarios. Therefore, atypical learning of implicit reward and atypical processing of social reward could account for the symptoms previously associated with reduced sensitivity to reward.

In summary, perceptual decision-making is a promising framework for investigating behavior in autism. By directly and systematically testing the effect of monetary reward on perceptual decision boundaries, this study revealed that autistic individuals exhibit suboptimal but typical integration of reward information, challenging the dominant view of a general deficit in reward processing in autism.

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Tables

	Autistic	Non-autistic
N	32	48
Age	28.58 (± 1.17)	28.13 (± 0.98)
AQ	25.68 (± 8.50)	17.02 (± 7.13)
IQ	100.19 (± 11.30)	99.79 (± 9.36)

Table 1. Descriptive statistics of the groups' characteristics. The table displays the means and standard errors of the age, Autistic Quotient, and non-verbal intellectual quotient (IQ) of the

autistic and non-autistic groups.

	Overall n	Comprehension question	Sensitivity	Criteria	Optimality	rt	Correlation
Sample size	$n_{autistic} = 32$ $n_{non-autistic} = 48$	$n_{autistic} = 30$ $n_{non-autistic} = 44$	$n_{autistic} = 30$ $n_{non-autistic} = 44$	$n_{autistic} = 30$ $n_{non-autistic} = 44$	$n_{autistic} = 30$ $n_{non-autistic} = 42$	$n_{autistic} = 30$ $n_{non-autistic} = 43$	$n_{autistic} = 27$ $n_{non-autistic} = 40$

Table 2. Description of the sample sizes in the overall experiment, 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.

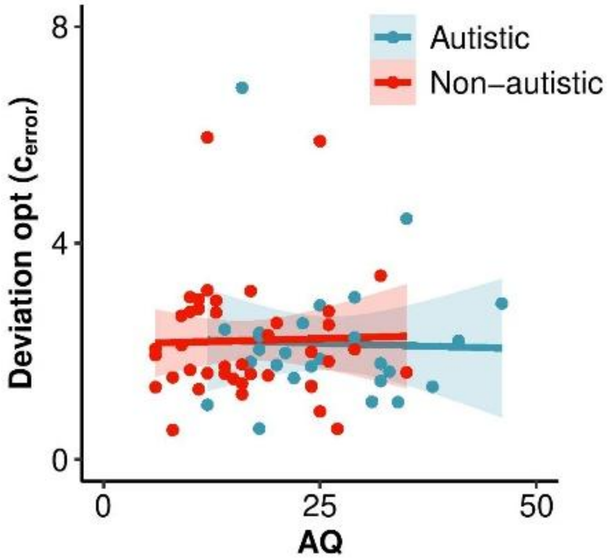
Supplementary Information

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

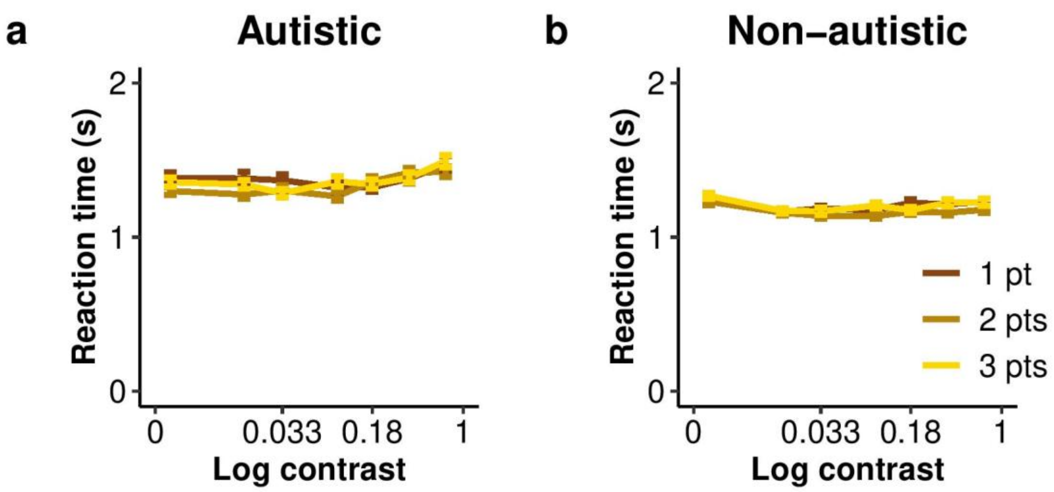
The analysis of the relation between AQ and c_{error} demonstrated no significant correlations for either the autistic ($r(25) = -0.03$, $p = .88$) or non-autistic ($r(38) = 0.03$, $p = .86$) group (**Supplementary Fig. 1**). These results support our previous finding by indicating that, just as for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



Supplementary Figure 1. Correlation between the deviation from optimality (c_{error}) and the Autistic Quotient (AQ). The data points represent individuals' suboptimality across contrast and block on the y-axis, and AQ score on the x-axis. The solid lines represent the linear regression line per group. The sample size consisted of 27 autistic and 40 non-autistic participants.

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. 2a-b**). Consistent with previous findings, the results show 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 Figure 2. Mean reaction time per group and contrast level for the autistic (a) and non-autistic (b) groups. The legend represents the reward attributed for correctly categorizing B. Data points show means across participants, and error bars represent ±SE. The sample size consisted of 30 autistic and 43 non-autistic participants.