Archival Report

Biological Psychiatry

Social Bayes: Using Bayesian Modeling to Study Autistic Trait–Related Differences in Social Cognition

Meltem Sevgi, Andreea O. Diaconescu, Marc Tittgemeyer, and Leonhard Schilbach

ABSTRACT

BACKGROUND: Autism is characterized by impairments of social interaction, but the underlying subpersonal processes are still a matter of controversy. It has been suggested that the autistic spectrum might be characterized by alterations of the brain's inference on the causes of socially relevant signals. However, it is unclear at what level of processing such trait-related alterations may occur.

METHODS: We used a reward-based learning task that requires the integration of nonsocial and social cues in conjunction with computational modeling. Healthy subjects ($N = 36$) were selected based on their Autism Quotient Spectrum (AQ) score, and AQ scores were assessed for correlations with model parameters and task scores.

RESULTS: Individual differences in AQ were inversely correlated with participants' task scores ($r = -.39$, 95% confidence interval [CI] [$-.68$, $-.13$]). Moreover, AQ scores were significantly correlated with a social weighting parameter that indicated how strongly the decision was influenced by the social cue ($r = -.42$, 95% CI [$-.66$, $-.19$]), but not with other model parameters. Also, more pronounced social weighting was related to higher scores ($r = .50$, 95% CI [.20, .86]).

CONCLUSIONS: Our results demonstrate that higher autistic traits in healthy subjects are related to lower scores in a learning task that requires social cue integration. Computational modeling further demonstrates that these trait-related performance differences are not explained by an inability to process the social stimuli and its causes, but rather by the extent to which participants take into account social information during decision making.

Keywords: Autistic traits, Bayesian modeling, Computational psychiatry, Reward-based learning, Social cognition, Social gaze

http://dx.doi.org/10.1016/j.biopsych.2015.11.025

Autism is characterized by profound impairments of social interaction and communication. These difficulties are thought to be related across the diagnostic divide to autistic trait–related differences in social perceptual or cognitive abilities (1). It has become clear in recent years that a striking dissociation exists between relatively intact explicit and severely impaired implicit social abilities (2). In other words, high-functioning individuals with autism learn to explicitly think about other persons' mental states, yet they still find it very difficult to engage in real-time social interactions with people without autism (3,4). Exactly which subpersonal processes show autistic trait–related differences and could explain everyday life social impairments is still a matter of substantial controversy. Recent studies have provided evidence that many putatively relevant processes, such as action perception, are intact in autism (5). Still, individuals with autism have striking impairments in social situations in everyday life, which raises the question of which and how processes other than basic perceptual mechanisms may come into play (6).

A currently prominent theoretical suggestion includes the assumption that the autistic spectrum might be specifically characterized by deficits of predictive coding or Bayesian inference (7,8). Predictive coding formulations of perception propose that expectations in higher brain areas generate top-down predictions that meet bottom-up, stimulus-related signals from lower sensory areas. The discrepancy between actual sensory input and predictions of that input is described as a prediction error. With regard to autism, it has been proposed that autistic traits might be related to higher sensory precision (i.e., a stronger reliance on [bottom-up] sensory evidence as opposed to [top-down] prior beliefs), which can lead to a failure of automatically contextualizing sensory information in an optimal and socially adequate fashion (9,10). Furthermore, the reliance on prior beliefs rather than sensory information might be particularly relevant in situations of high uncertainty, such as direct social interactions with others, as social agents are arguably the most difficult "things" to predict (10). This theoretical proposition resonates with clinical descriptions of patients with autism as having a particular dislike for situations of direct social interaction with others, whereas situations of social observation are described as less difficult (4).

In light of recent findings that demonstrate relatively intact perceptual processes in autism, it might be precisely the integration of bottom-up and top-down processes during social interactions and exploitation of social cues provided by others during decision making that could be particularly relevant to understanding the social impairments in autism. In other words, although autistic traits may not be associated with disturbances of basic perceptual and learning processes, it is conceivable that such traits may affect whether and to what extent social information influences decision making and what behavior is actually shown. From a predictive coding perspective, there are two possible pathologies. There could be deficits in predicting and inferring the mental states of others, or, alternatively, these inferences could be unable to influence behavior because they are afforded an impoverished weight or precision.

Recent progress in computational modeling has demonstrated that Bayesian models can be used to formally investigate perceptual and cognitive mechanisms that underlie social behavior when explicit social advice is provided to study participants (11). In particular, it has been shown that humans employ hierarchical generative models to make inferences about the changing intentions of others when attention is explicitly directed toward them and that they integrate estimates of advice accuracy (i.e., the correctness of the advice, which can be valid or misleading depending on the conflicting interests of the players) with nonsocial sources of information when making decisions. In Bayesian terms, this integration corresponds to an optimal weighting of prosocial and nonsocial cues in terms of their relative precision when making decisions.

In the present study, we build on this research by applying hierarchical Bayesian modeling to behavioral data from a novel version of a probabilistic learning paradigm. This paradigm included a social gaze cue about whose relevance no explicit information was provided in order to investigate autistic trait–related differences in the extent to which healthy individuals integrate and use this piece of social information during task performance. We hypothesized that autistic traits are related to differences in the extent to which individuals are influenced by social cues (i.e., their precision), rather than a general inability to process social cues and their putatively underlying mental states. On the behavioral level, this hypothesis should result in higher total task scores for individuals lower in autistic traits, as they should be more easily able to exploit the additional social information. In terms of the underlying cognitive processes, we hypothesized that this behavioral advantage might be subserved by differences in the effect that social information has on decision making, which would be inversely related to autistic traits. We further predicted that using the social cue should be more difficult under volatile conditions and differentially so for individuals with higher autistic traits.

METHODS AND MATERIALS

Participants

In light of evidence suggesting that autistic traits are distributed as a continuum across the general population and are known to show identical etiology across the diagnostic divide (1), we chose to study healthy participants based on their score on the German translation of the Autism Quotient Spectrum (AQ) questionnaire (12). This experimental approach of studying autistic traits in neurotypical subjects makes it possible to make inferences about the etiology of autistic traits without potential confounds from various comorbid conditions often noted in patients with autistic spectrum disorders. To capture the extremes of the distribution and have a balanced proportion of participants with high and low AQ scores, 36 subjects were prescreened and invited to participate based on their AQ scores up to 25 (19 men; age range, 20–37 years; mean age 26.25 years). It has been shown that AQ has good discriminative validity at a threshold of 26 (13). Participants did not have any history of neurologic and psychiatric disorders and were recruited by using a preexisting database of the Max Planck Institute for Metabolic Research comprising healthy native German volunteers. The distribution of AQ scores was as follows: range, 7–23; mean 15.72; SD 5.09. All participants gave informed consent before the beginning of the experiment.

Experimental Paradigm

The card game used in our study, which had been originally designed as two cards with associated winning probabilities (14,15), was combined with a face cue presented in the center of the screen (Figure 1A). The eye gaze direction of the face was manipulated to change during each trial and to be directed toward one of the cards before participants were allowed to make their choice. As a result, two things needed to be learned in the task: first, whether the reward is associated with the green card or the blue card; second, whether the gaze shift is directed toward the card that is rewarded. The probability of whether or not the face actually looked toward the winning card on a given trial (i.e., gaze accuracy) was systematically manipulated in accordance with a probabilistic schedule as well (Supplement 1). Both the card and the gaze accuracies were varied independently of one another (Figure 1B, C). The phases in which the trials have cues with unstable accuracy are referred to as volatile phases. In the first half of the experiment (trials 1–60), card accuracy was stable and high, whereas in the second half (trials 60–120), it followed a volatile phase. For the gaze accuracy, the volatile phase took place during trials 30–70. The probabilistic schedule for the gaze accuracy was reversed for half of the subjects to avoid block order effects. Positions of the cards (left or right) were determined randomly.

In the instructions, subjects were informed about the cards' having winning probabilities, which could change during the experiment and which were independent of the reward magnitude that was displayed on them. On each trial, there would be only one correct card, and if subjects chose the correct card, they would receive the score (random numbers between 1 and 9) that had been displayed on it. Subjects were instructed that they would earn an extra amount of money depending on their score at the end of the experiment. Finally, participants were informed about the presence of a face on the screen, which was explained by stating that it was supposed to make the visual display "more interesting." Participants did

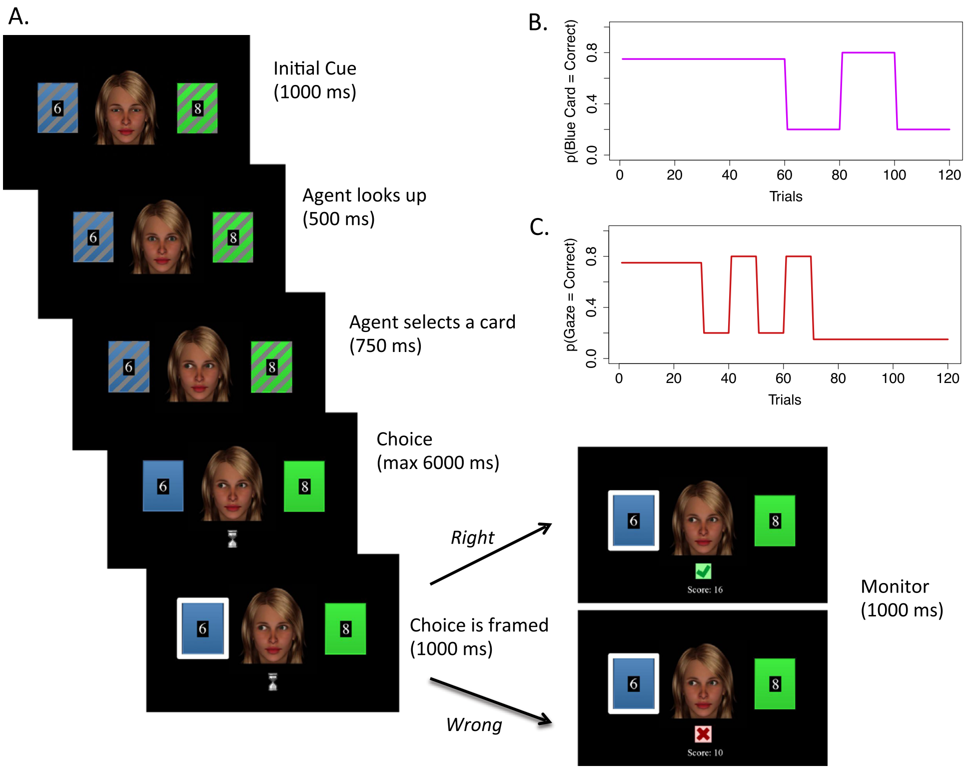

Figure 1. The experimental design. **(A)** Subjects can make a choice once the lines on both cards disappear. If the choice is right on that trial, a green tick is displayed, and the reward value of the right card is added to the total score. If the choice is wrong, a red cross is displayed, and the score remains the same. Probability schedules: **(B)** probability of the blue card being correct (i.e., card accuracy) and **(C)** probability of the gaze showing the correct card (i.e., gaze accuracy).

not receive any other information about the face. After the experiment, subjects filled out a brief questionnaire.

Perceptual and Response Models

The "observing the observer" approach provides a complete mapping from experimental stimuli to observed responses by inverting the perceptual model and the response model (16). An extension of this approach is a generative model called hierarchical Gaussian filtering (HGF), which accounts for deterministic and probabilistic relationships between the environment and perceptual states (17). We used a perceptual-response model pair to infer subjects' beliefs about the stimuli. We modeled congruency of response with advice (i.e., the advice given by the social cue [the gaze]), using HGF combined with a response model as implemented by Diaconescu *et al.* (11); Figure 2 is a graphic representation. This approach allows the estimation of hierarchically coupled hidden states that describe subjects' learning about the environmental statistics—the probability and the volatility of the card and gaze cues—based on their responses. These subjective beliefs are weighted by their precision to form the basis of a response model (of the observed behavior) as explained in detail subsequently. Supplement 1 contains a detailed description of the perceptual models used here.

Precision Weighted Response Model. We applied the HGF to derive subject-specific accuracy and volatility estimates for card and gaze in a parallel manner. On a given trial, t, subjects generated a combined belief, $b^{(t)}$, after weighting the posterior expectation of inferred card and gaze accuracies, $\mu^{(t)}_{1,card}$ and $\mu^{(t)}_{1,\,gaze}$, to generate actions in the following manner:

$$w^{(t)}_{gaze} = \frac{\zeta\pi^{(t)}_{1,gaze}}{\zeta\pi^{(t)}_{1,gaze}+\pi^{(t)}_{1,card}},\quad w^{(t)}_{card} = \frac{\pi^{(t)}_{1,card}}{\zeta\pi^{(t)}_{1,gaze}+\pi^{(t)}_{1,card}} \tag{1}$$

$$b^{(t)} = w^{(t)}_{gaze}\,\mu^{(t)}_{1,gaze}+w^{(t)}_{card}\,\mu^{(t)}_{1,card} \tag{2}$$

where w_{gaze} and w_{card} are effective precisions of gaze and card cues, ζ is the weight on the precision of inferred gaze accuracy or the additional bias toward the social cue, and $\pi^{(t)}_{1,gaze}$ and $\pi^{(t)}_{1,card}$ are precisions (inverse variances) at the first level for gaze and card accuracies, respectively. Because the first-level estimates are assumed to follow a Bernoulli distribution, one can calculate the precision at each trial by

$$\pi^{(t)}_{1,gaze} = \frac{1}{\mu^{(t)}_{1,gaze}\left(1-\mu^{(t)}_{1,gaze}\right)},\quad \pi^{(t)}_{1,card} = \frac{1}{\mu^{(t)}_{1,card}\left(1-\mu^{(t)}_{1,card}\right)} \tag{3}$$

The probability of taking the gaze advice was assumed to be a unit square sigmoid function:

$$p\left(y^{(t)}=1|b^{(t)}\right) = (b^{(t)})^{\beta}/((b^{(t)})^{\beta}+(1-b^{(t)})^{\beta}) \tag{4}$$

where β is a function of the third-level volatility estimate or μ_3:

$$\beta = \exp\left(-\mu^{(t)}_{3,gaze}\right)+\exp(-\mu^{(t)}_{3,card}) \tag{5}$$

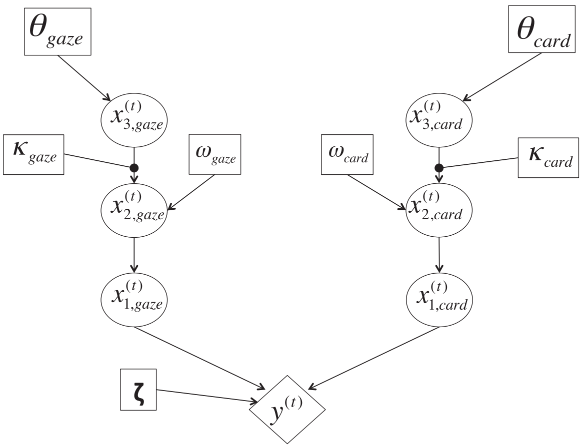

Figure 2. Graphic depiction of two parallel learning systems that were assumed to influence the choice behavior. For any trial t, $x_3^{(t)}$ follows a Gaussian random walk such that $p\left(x_3^{(t)}\right) \sim \mathcal{N}\left(x_3^{(t-1)}, \theta\right)$. The first level state variable, $x_1^{(t)}$, is the accuracy at that trial and is a sigmoid transform of the second level state variable, $x_2^{(t)}$, which also follows a Gaussian distribution: $\mathcal{N}\left(x_2^{(t-1)}, \exp\left(\kappa x_3^{(t)} + \omega\right)\right)$, where the variance term includes two parameters: ω is the fixed component of the step size variance, and κ accounts for the coupling between the third and the second levels. The response model parameter ζ represents the weight on the precision of the inferred gaze accuracy.

Parameter Estimation. HGF is a generative model of the hidden states causing the sensory inputs. Maximum a posteriori estimates of the parameters are obtained using an approximate variational Bayesian scheme. It can be downloaded as a part of the TAPAS software collection (http://www.translationalneuromodeling.org/tapas/). The update equations take the form of precision-weighted prediction errors following a form similar to an extended Kalman filter and are hence analytically trackable. Beliefs at every level in the hierarchy are updated with a step size equivalent to the prediction error times a ratio of precisions (precision of the data in the numerator and precision of the prediction in the denominator). For details of the updated equations and the variational Bayesian inversion scheme, see Mathys *et al.* (17) and Daunizeau *et al.* (16). All parameters (θ_{gaze}, θ_{card}, κ_{gaze}, κ_{card}, ω_{gaze}, ω_{card}, ζ) and state variables were estimated for each subject by using a quasi-Newton minimization algorithm as implemented in HGF version 3 running on MATLAB 7.12 (The MathWorks, Inc., Natick, Massachusetts).

Given that we assumed the autistic spectrum to be characterized by differences in the extent to which individuals weight social information rather than an inability to process social information, we predicted that autistic traits (as measured by AQ scores) would be associated with the degree to which individuals weight the gaze cue while making decisions. More precisely, the model parameter ζ was expected to be negatively correlated with AQ scores. Therefore, a large value of ζ signals that a participant preferentially bases his or her decisions on the social advice (i.e., the gaze cue) compared with other cues during decision making. To test the association of autistic traits with the extent of processing and weighting the gaze cue, we applied a multivariate regression analysis on the AQ scores by using the model parameters of the winning model as predictors (see later for model space). Because the parameter ζ is estimated in log space, we included it in the regression in log space as well. We performed all correlations with bootstrapping (2000 bootstraps) and 95% confidence intervals (CIs). To demonstrate the specificity of the significant predictors to the AQ scores, we performed a full model analysis including the following other variables: sex, age, systemizing quotient, empathy quotient, and IQ (verbal) scores (Table 1).

In addition to this original model (model 1), we included a second model to test if the subjects did not take the gaze accuracy into account when making decisions (model 2). A third model that includes a perceptual model with fixed parameters paired with a decision noise response model was also included (model 3) (Supplement 1).

Other Behavioral Measures

We assessed the relationship between AQ scores and individual total task scores as the ability to exploit the additional social information to contribute to task performance. It is possible that the volatility of the input structure may influence subjects' inference about the advice validity and subsequent decision to take the advice into account that would influence the scores obtained. The influence of probability (high vs. low) and volatility (stable vs. volatile) of the gaze cue on the performance was evaluated and compared between two AQ groups, which were obtained using a median split procedure (median AQ = 15). The association between autistic traits and advice-taking behavior on volatile low-probability gaze cue trials was evaluated separately by means of correlation analyses.

RESULTS

Model Comparison

The model selection is based on the model evidence, which is a principled measure of the balance between model fit and model complexity (18). Model comparison was in favor of model 1 (exceedance probability of .9408), suggesting that a hierarchical Bayesian model in which participants weighted both social and reward-related information best described subjects' responses. The exceedance probabilities for model 2

Table 1. Descriptive Data of Participants

AQ Group	No. Subjects	Sex, M/F	Age, Years	AQ	SQ	EQ	IQ (Verbal)
High AQ	18	9/9	25.5 ± .7	20.4 ± .5	27.1 ± 2	41.1 ± 2.1	101.9 ± 2.1
Low AQ	18	10/8	27 ± 1	11.1 ± .4	23.9 ± 2.1	44.3 ± 2.6	103.2 ± 2.7

Data are given as *n* or mean ± SEM.

AQ, Autism Quotient Spectrum; EQ, empathy quotient; F, female; M, male; SQ, systemizing quotient.

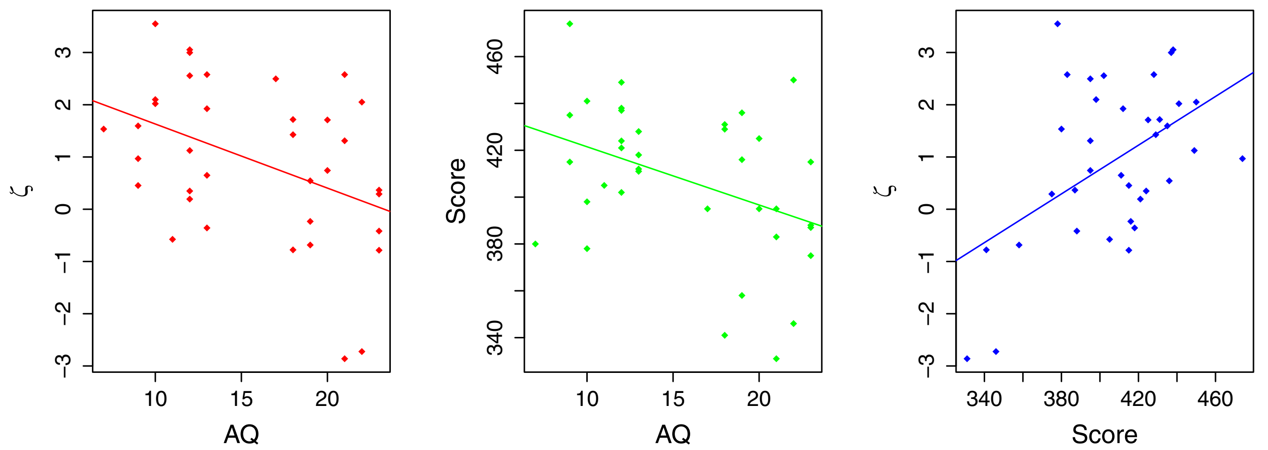

Figure 3. Relationship of total scores, Autism Quotient Spectrum (AQ) and ζ. (Left panel) Negative correlation between ζ parameter and AQ traits ($r = -.42$, 95% confidence interval [CI] [−.66, −.19]). (Middle panel) Negative relationship between subjects' AQ traits and their score at the end of the task ($r = -.36$, 95% CI [−.68, −.13]). (Right panel) Positive correlation between total score and ζ parameter ($r = .5$, 95% CI [.20, .86]).

and model 3 were .0384 and .0208, respectively. We also evaluated performance of the three models with balanced accuracy. We observed a balanced accuracy of .61 for model 1, the winning model; .54 for model 2; and .58 for model 3, further corroborating our findings.

Model Parameters as Predictors of AQ Scores

A multivariate regression was conducted to investigate an assumed relationship of gaze-cue related model parameters (θ_{gaze}, κ_{gaze}, ω_{gaze}, ζ) of the winning model and AQ scores. The analysis shows that ζ values (i.e., weighting the gaze) did significantly predict the AQ scores ($\beta = -1.60$, $t_{31} = -2.77$, $p = .0095$). Other parameters—θ_{gaze} ($\beta = 12.37$, not significant), κ_{gaze} ($\beta = -.66$, not significant), and ω_{gaze} ($\beta = -.18$, not significant)—were not significant predictors ($F_{4,31} = 2.02$, $R^2 = .21$). Because negative coefficients in the multivariate regression analysis do not mean that there actually is a negative correlation between the response and the predictor, we investigated the direction of the association between AQ scores and the advice weighting parameter ζ by performing a correlation analysis (Figure 3, left panel). The Pearson correlation coefficient between ζ and AQ scores was −.42 (95% CI [−.66, −.19]).

To address the specificity of ζ to AQ scores, we performed a full model: a multivariate regression analysis including explanatory variables of AQ, IQ, systemizing quotient, empathy quotient, age, and sex was used to predict the social gaze weighting parameter (ζ). The analysis shows that only AQ scores significantly predicted the parameter ζ ($\beta = -.11$, $t_{31} = -2.18$, $p = .037$). The other descriptive scores—IQ ($\beta = .02$,

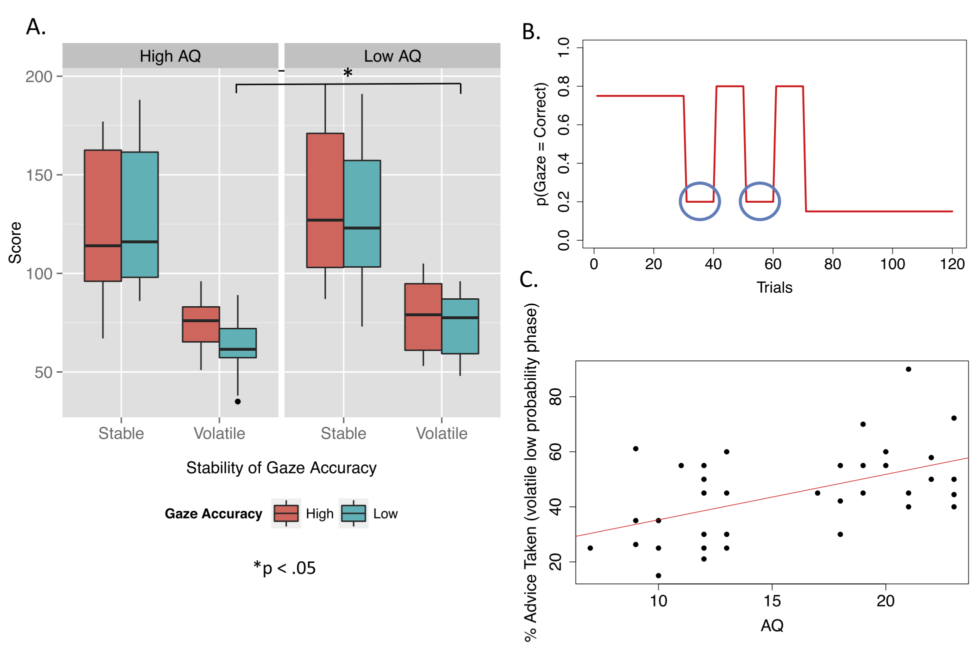

Figure 4. Influence of structure of the environment on the behavior. **(A)** Scores obtained by high and low Autism Quotient Spectrum (AQ) groups in different phases of the experiment based on the features of the gaze cue (high × low gaze accuracy and stable × volatile periods of gaze accuracy). **(B)** Difference is significant (*$p = .034$) in the volatile low accuracy phase (circled area). **(C)** During the same phase, the number of trials in which the subjects took the advice (i.e., chose the card that is indicated by the highly misleading gaze) was correlated with AQ traits ($r = .52$, 95% confidence interval [.29, .75]).

not significant), empathy quotient ($\beta = -.02$, not significant), systemizing quotient ($\beta = .003$, not significant), age ($\beta = .09$, not significant), and sex ($\beta_{male} = .46$, not significant)—were not significant predictors ($F_{6,29} = 1.814$, $R^2 = .27$).

Relationship of Total Scores, AQ, and ζ

Individual differences in AQ scores were significantly correlated with participants' total scores ($r = -.39$, 95% CI [−.68, −.13]) (Figure 3, middle panel). Also, a relationship between total scores and ζ was observed such that a more pronounced weighting of advice was related to higher total scores ($r = .50$, 95% CI [.20, .86]) (Figure 3, right panel).

Association Between AQ Scores and the Utility of Misleading Advice in a Volatile Environment

Figure 4A illustrates the performance in each phase of the gaze accuracy. As expected, when the gaze accuracy is volatile, it is difficult to learn—hence yielding lower scores. Moreover, we observed a significant difference between two groups during the volatile low probability phase (Welch's t test [$t_{33} = 2.21$, $p = .034$]). These phases are highlighted with circles in Figure 4B. Similarly, AQ correlated with the number of trials where the subjects took the advice ($r = .52$, 95% CI [.29, .75]) in the same phase (Figure 4C). Therefore, even during the volatile phases of the experiment, the low AQ group was able to take advantage of misleading advice by avoiding it.

DISCUSSION

In this study, we applied hierarchical Bayesian modeling to investigate autistic trait–related differences in the extent to which healthy individuals integrate and make use of gaze cues in a probabilistic reward learning task. For optimal performance, our task required following both the card and the gaze cues and combining these two sources of information, even though instructions provided very little information about the nature and relevance of the gaze cues, in contrast to other studies using explicit forms of social advice (11,14). As expected, our results demonstrate an inverse relationship between autistic traits and total task scores obtained by study participants, such that individuals higher in autistic traits obtained lower total task scores.

To provide a mechanistic explanation for such autistic trait–related differences in performance, we applied computational modeling to the behavioral data. We were interested to model perceptual as well as higher-order processing of both card and gaze cues and, in particular, their relationship to action selection (i.e., the extent to which individuals were actually biased by the social information provided on a trial-by-trial basis). Results of our computational analyses demonstrate striking evidence for autistic trait–related differences, such that individuals lower in autistic traits are influenced more by the gaze cue, as indicated by a negative relationship between the response model parameter ζ and autistic traits. Our results also show a positive relationship between ζ and the total individual scores obtained in the experiment, which indicates that reliance on the social information was actually what was helping subjects lower in autistic traits to obtain higher scores. Furthermore, our results indicate that individuals high in autistic traits had particular difficulties using the social advice under volatile conditions.

By providing these striking new insights into autistic trait–related differences in social cognition, we believe that our study is most relevant to current discussions concerned with mechanistic explanations of autism. Predictive coding theories have reconstructed autism in terms of high-level attenuated precisions relative to sensory precision (9), which results in an enhanced weighting of prediction errors (10) and a loss of the selective force when processing a context with multiple cues (19). In the present study, Bayesian models provide an important avenue (7) that can help identify whether autistic trait–associated alterations lie in the reliance on prior knowledge or the optimal update of prior information during learning. In our Bayesian formulation, we addressed this issue by assessing possible relationships of perceptual and response model parameters with autistic traits. However, no relationship between the perceptual model parameters and these traits was found, which is suggestive of an intact inference machinery. However, the response model parameter ζ, which constitutes the weight on the precision of inferred gaze probability, reflected that participants who scored higher on the autism questionnaire could not take advantage of the learned precision estimates of the social cue when mapping representations to beliefs. Taken together, these results suggest that the mechanisms of estimating the precision of social information do not differ, but that the application of new, updated priors depends on the level of autistic traits. These findings appear consistent with a recent suggestion by Palmer *et al.* (20), who proposed that autism may not impair the ability to process social information per se, but rather lead to differences in how the relevant representations are weighted for action selection.

In light of other propositions, which hold that autistic trait–related impairments of social cognition may be particularly relevant in complex and unpredictable situations (19), we further investigated whether autistic traits were also related to task performance during phases of the experiment, which included volatile and misleading gaze cues. Our data show that this particularly unstable environment made it more difficult for subjects with higher autistic traits to use the social cue while making decisions. This kind of influence of volatility on behavior parallels results from previous studies, which report that an unpredictable context makes it more difficult for individuals with autism to use social cues in an appropriate way (21). Therefore, our finding can be seen as evidence for difficulties in contextualizing social cues in light of high uncertainty.

To the best of our knowledge, our study is the first to use a hierarchical Bayesian model in the context of autistic traits. The modeling approach that we implemented here is a promising method for capturing individual differences in the learning and integration of social information. Given the heterogeneity of the population, this could be particularly useful for identifying subgroups that may map onto distinct mechanisms of impaired social interaction in autism. The "observing the observer" approach has been demonstrated to be useful for inference in hidden states and parameters that shape interindividual differences in learning (22). Hierarchical Bayesian models of learning such as the HGF linked to action selection have been implemented in several different learning contexts (11,23,24). Our results indicate that Bayesian models may be particularly powerful in providing mechanistic explanations of social difficulties, which are particularly relevant to an understanding of psychiatric disorders (4,25,26). Advances in computational psychiatry (27–30) and studies such as this one could contribute to mechanistic formulations of psychopathology.

We cannot rule out intact precision-weighted prediction error processing in patients with autism, as our sample comprised healthy subjects. Also, one can speculate that in a sample comprising patients with autism, impaired inference about the social cue in addition to the reduced reliance on it could be observed. Therefore, future research should include testing patients with a formal diagnosis of autism to explore whether the observed differences hold across the entire spectrum. Furthermore, the experimental paradigm introduced here and our analytic approach could be used together with neuroimaging to investigate which activity and connectivity profiles in brain regions relevant for social cognition underlie the observed autistic trait–related behavioral differences.

In conclusion, taken together, the results of our study demonstrate autistic trait–related behavioral differences in a task that requires the integration of nonsocial and social information. Using hierarchical Bayesian modeling, we show that these performance differences are not subserved by impairments of basic perceptual and learning processes, which is consistent with recent findings in autism (5), but are rather related to the extent to which individuals are actually influenced by the social information during decision making. In other words, autistic traits may not impair the ability to process social information per se, but rather by a low weighting or precision of social cues during decision making.

ACKNOWLEDGMENTS AND DISCLOSURES

This work was supported by the German Research Foundation Clinical Research Group 219 (MT) and Transregional Collaborative Research Center 134 (MT, LS) and the Max Planck Society (MS, LS).

The authors gratefully acknowledge Christoph Mathy's help and support during this project.

The authors report no biomedical financial interests or potential conflicts of interest.

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Received Jul 17, 2015; revised Nov 11, 2015; accepted Nov 30, 2015.

Supplementary material cited in this article is available online at http://dx.doi.org/10.1016/j.biopsych.2015.11.025.

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