

Cognitive Mechanisms of Aberrant Self-Referential Social Perception in Psychosis and Bipolar Disorder: Insights from Computational Modeling

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Abstract

Background and Hypothesis: Individuals with schizophrenia (SZ) and bipolar disorder (BD) show disruptions in self-referential gaze perception—a social perceptual process related to symptoms and functioning. However, our current mechanistic understanding of these dysfunctions and relationships is imprecise.

Study Design: The present study used mathematical modeling to uncover cognitive processes driving gaze perception abnormalities in SZ and BD, and how they relate to cognition, symptoms, and social functioning. We modeled the behavior of 28 SZ, 38 BD, and 34 controls (HC) in a self-referential gaze perception task using drift-diffusion models (DDM) parameterized to index key cognitive components: drift rate (evidence accumulation efficiency), drift bias (perceptual bias), start point (expectation bias), threshold separation (response caution), and non-decision time (encoding/motor processes).

Study Results: Results revealed that aberrant gaze perception in SZ and BD was driven by less efficient evidence accumulation, perceptual biases predisposing self-referential responses, and greater caution (SZ only). Across SZ and HC, poorer social functioning was related to greater expectation biases. Within SZ, perceptual and expectancy biases were associated with hallucination and delusion severity, respectively.

Conclusions: These findings indicate that diminished evidence accumulation and perceptual biases may underlie altered gaze perception in patients and that SZ may engage in compensatory cautiousness, sacrificing RT to preserve accuracy. Moreover, biases at the belief and perceptual levels may relate to symptoms and functioning. Computational modeling can, therefore, be used to achieve a more nuanced, cognitive process-level understanding of the mechanisms of social cognitive difficulties, like gaze perception, in individuals with SZ and BD.

Keywords: *schizophrenia, psychosis, bipolar disorder, gaze perception, social cognition, computational modeling, drift diffusion model*

Introduction

Individuals with schizophrenia (SZ) and bipolar disorder (BD) display chronic, medication-resistant functional impairments in social, familial, and role domains^{1–5}. Major drivers of functional impairments are persistent deficits in social cognition, which allow individuals to process and understand information about other people^{6–8} and occur regardless of illness phase^{9,10}.

One critical determinant of social cognition is *self-referential gaze perception*—the ability to judge whether others are looking at us^{11,12}. Gaze information is used with cues like facial emotion and head orientation to understand others' inner states¹³. This informs decision-making, behavior, and functioning^{14,15}. Yet, in SZ and BD, these abilities are disrupted. Patients tend to make slower^{16–21}, less accurate^{17,20,22}, and/or less precise judgments about others' gaze^{23–27}, and show self-referential biases toward over-endorsing eye contact^{23–26,28,29,29,30}. These disruptions relate to poorer general^{23,28,29} and social cognition^{16,23,24,27,29}, and greater positive and negative symptoms (in SZ)^{22,23,26,28}.

The clinical and functional relevance of gaze perception deficits in SZ and BD demand a deeper mechanistic account. Yet, perceptual choices like gaze perception depend on several intertwined processes, including sensory encoding, initial expectations, evidence accumulation, response caution, and motor execution³¹. Traditional measures like accuracy and response time (RT) are ill-suited to identify these mechanistic differences. One reason for this, as detailed below, is that multiple pathways can lead to a single disruption in gaze perception. Therefore,

multiple explanations are possible. For instance, individual differences in response caution and/or processing efficiency for self-referential choices can produce changes in task-averaged RT and accuracy.

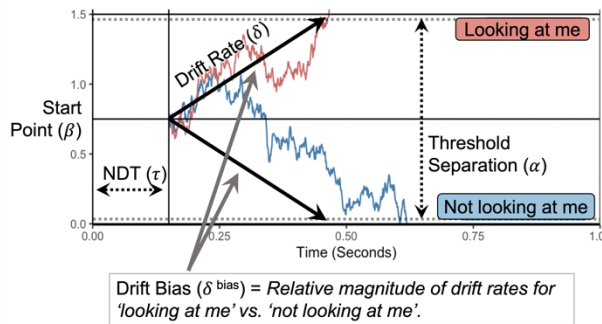
Computational modeling provides a solution to characterizing these different processes. Here we employed drift-diffusion models (DDM) to characterize how the mechanisms of gaze perception are disrupted in SZ and BD, and relate to general/social cognition, SZ symptoms, and social functioning.

According to the DDM, when deciding whether someone is looking at them or not, individuals accumulate noisy sensory evidence about both choices (Figure 1A). A decision is made once evidence reaches a threshold for either choice. Different cognitive processes are linked to different DDM parameters (Figure 1B), supporting various pathways gaze perception disruptions in patients (Figure 1C). The *drift rate* determines the direction and rate of evidence accumulation, indexing how efficiently evidence is accumulated to determine if someone is looking at them. Lower drift rates mean slower, more error-prone choices (Figure 1.C1-C6). The separation between choice thresholds determines how much evidence is needed before making a decision. Higher separation means more evidence and, consequently, slower and less error-prone choices (Figure 1.C3/C5-C6). Thus, the *threshold separation* determines one's cautiousness in trading speed for accuracy. Two mechanisms of the DDM can produce self-referential biases. The first is the *start point* for evidence accumulation. If evidence accumulation begins closer to one choice threshold, responses will show a bias and faster RTs for that choice (Figure 1.C3/C6). Thus, the start point determines one's initial expectancy bias in detecting self-referential gaze. The second is the *drift bias*: an asymmetry in the relative magnitudes of drift rates for direct and indirect gaze. If participants process gaze information as "looking at me" more efficiently, this

can reduce the evidence accumulation rate for indirect gaze, creating a perceptual bias toward self-referential responses (Figure 1.C4-C6). Finally, the *non-decision time* (NDT) captures sensory and motor processes that are separate from the deliberation process. Longer NDT's mean longer RT's (Figure 1.C2).

We leveraged extant data ^{16,17,20,21} to characterize cognitive processes driving gaze perception using a DDM framework ³². We hypothesized that SZ and BD would show less efficient evidence accumulation than HC because patients exhibit lower drift rates across several cognitive tasks ³³⁻³⁹. We explored group differences in threshold separation, start point, and drift bias to delineate among various mechanistic explanations illustrated in Figure 1C. Finally, we examined the mechanisms of relationships between gaze perception and general/social cognition, positive/negative symptoms in SZ, and social functioning by exploring associations with DDM parameters.

A) Overview of Drift Diffusion Model (DDM)

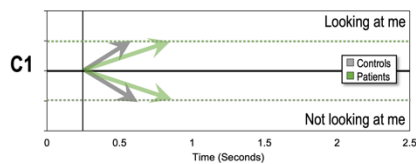


B) Definitions of DDM Parameters

Parameter	Notation	Psychological Description	Mathematical Description
Drift Rate	δ ("delta")	How efficiently people accumulate evidence for 'at me' vs. 'not at me' choice options.	Mean rate of evidence accumulation towards either option.
Threshold Separation	α ("alpha")	Level of caution in trading speed for accuracy. Larger thresholds lead to slower, more accurate choices.	Determines the distance between the choice thresholds for choice options.
Start Point	β ("beta")	Belief-driven <u>expectancy bias</u> people have about others looking 'at me' vs. 'not at me'.	How close to either choice threshold people start accumulating evidence from.
Drift Bias	δ_{bias} ("delta bias")	Data-driven <u>perceptual bias</u> . Relative magnitude of evidence accumulation efficiency for looking 'at me' vs. 'not at me' choices.	Average of drift rate (δ) for 'at me' vs. 'not at me' choices.
Non-Decision Time (NDT)	τ ("tau")	Time dedicated to non-decision processes, like sensory encoding and motor execution.	Controls the shifting of RT distribution.

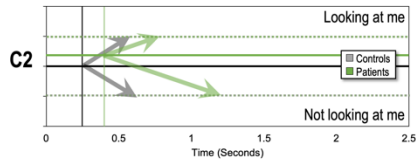
C) Explanations of Existing Findings Through a DDM Lens

Observation 1: Patients are slower, less accurate, and unbiased

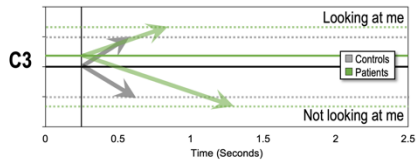


Parameter	Disruptions in Patients (vs. Controls)	Interpretation
Drift Rate	Lower drift rate for both choices	General processing inefficiency
Threshold Separation	--	--
Start Point	--	--
Drift Bias	--	--
NDT	--	--

Observation 2: Patients are slower, less accurate, and biased toward "looking at me"

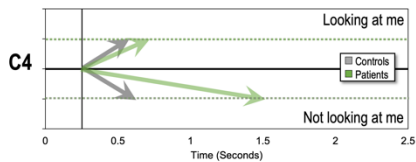


Parameter	Disruptions in Patients (vs. Controls)	Interpretation
Drift Rate	Lower drift rate for both choices	General processing inefficiency
Threshold Separation	--	--
Start Point	Closer to "looking at me"	Expectancy bias toward "looking at me"
Drift Bias	--	--
NDT	Longer NDT	Slower sensory/motor processes

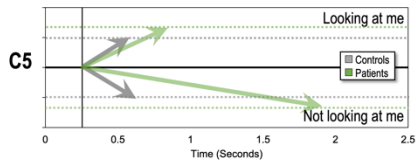


Parameter	Disruptions in Patients (vs. Controls)	Interpretation
Drift Rate	Lower drift rate for both choices	General processing inefficiency
Threshold Separation	Larger separation	Greater caution
Start Point	Closer to "looking at me"	Expectancy bias toward "looking at me"
Drift Bias	--	--
NDT	--	--

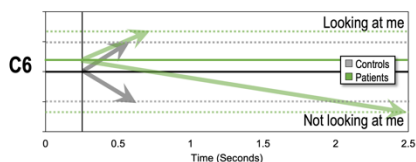
Observation 3: Patients are slower and less accurate (especially for indirect gaze), and biased toward "looking at me"



Parameter	Disruptions in Patients (vs. Controls)	Interpretation
Drift Rate	Lower drift rate for both choices	General processing inefficiency
Threshold Separation	--	--
Start Point	--	--
Drift Bias	Magnitude of drift rate for "at me" > "not at me"	Perceptual bias toward "looking at me"
NDT	--	--



Parameter	Disruptions in Patients (vs. Controls)	Interpretation
Drift Rate	Lower drift rate for both choices	General processing inefficiency
Threshold Separation	Larger separation	Greater caution
Start Point	--	--
Drift Bias	Magnitude of drift rate for "at me" > "not at me"	Perceptual bias toward "looking at me"
NDT	--	--



Parameter	Disruptions in Patients (vs. Controls)	Interpretation
Drift Rate	Lower drift rate for both choices	General processing inefficiency
Threshold Separation	Larger separation	Greater caution
Start Point	Closer to "looking at me"	Expectancy bias toward "looking at me"
Drift Bias	Magnitude of drift rate for "at me" > "not at me"	Perceptual bias toward "looking at me"
NDT	--	--

Figure 1. Overview of DDM and DDM accounts of extant findings. DDM application to gaze perception; B) Definitions of DDM parameters; C) Several plausible hypotheses that could account for existing data on gaze perception in SZ and BD. Dashed horizontal lines designate decision boundaries, where the vertical distance between decision boundaries represents the threshold separation (i.e., response caution) parameter.

Methods

Participants

The present study re-examined previously published datasets^{16,17,20,21} consisting of 28 SZ, 38 BD, and 34 HC participating in two separate waves of a larger study examining social processing in SZ (“SZ sub-study” [28 SZ, 18 HC]) and BD (“BD sub-study” [38 BD, 16 HC]). Participants were recruited from the University of Michigan Prechter Bipolar Longitudinal Study, community advertisements, and local clinics. Participants had no history of medical conditions with neurological sequelae, visual acuity of 20/30 or better on Snellen chart, and no recent substance use disorder (patients had no substance abuse or dependence in past year, HC in last five years). BD met criteria for bipolar I and SZ met criteria for schizophrenia or schizoaffective disorder. HC had no history of axis I disorders and no first-degree relatives with bipolar or psychotic disorders.

Procedure

Participants gave written informed consent and were compensated for participation. The study received approval from the Institutional Review Board at the University of Michigan Medical School. Study procedures included: diagnostic assessments and clinical ratings by

trained assessors, neuropsychological tests of general/social cognition, self-reports, and a behavioral gaze discrimination task. The task was completed during the acquisition of electroencephalography (EEG) data, but EEG analysis is outside the scope of this paper.

Measures

Assessments

Diagnoses were confirmed by trained assessors using the Structured Clinical Interview for DSM-IV-TR⁴⁰ or Diagnostic Interview for Genetic Studies⁴¹. In the SZ sub-study, symptoms were assessed using the Scale for Assessment of Positive Symptoms (SAPS⁴²) and the Scale for Assessment of Negative Symptoms (SANS⁴³). Inter-rater reliability was > 80% for diagnoses and clinical ratings. Participants in the SZ sub-study completed measures of general cognition (Brief Assessment of Cognition in Schizophrenia [BACS]^{44,45}), emotion-related social cognition (Mayer-Salovey-Caruso Emotional Intelligence Test [MSCEIT];⁴⁶), and real-world social functioning (Social Adjustment Scale Self-Report, Social/Leisure scale [SASSR-Social]^{47,48}; inverse-coded). BACS subtests were z-scored relative to published age- and gender- norms of a normative HC sample and averaged to obtain a composite measure of general cognition⁴⁵. MSCEIT subscales were converted to age- and gender-corrected standard scores⁴⁶, z-scored relative to the full sample, and averaged to obtain a composite measure of emotion-based social cognition.

We focused on three symptom domains in SZ—delusions, hallucinations, and an amotivation factor in the negative symptom domain. Hallucinations are thought to stem from initial biases applied to one's perceptual experiences⁴⁹, while delusions may stem from biases more purely at the expectation or belief level^{50,51}. Both forms of bias can potentially play a role in gaze perception. Because DDM parameters can capture belief and perceptual biases through

the start point and drift bias parameters⁵², respectively, we examined relationships between severity of hallucinations (sum of SAPS hallucination items), delusions (sum of SAPS delusion items), and DDM parameters to examine the potential mechanisms of relationships between gaze perception and positive symptoms in SZ. Prior data supports a 2-factor structure of negative symptoms consisting of an amotivation factor (avolition, anhedonia, asociality) and a diminished expression factor (flat affect, alogia)^{53–57}. Because the former may have implications for social cognition, general functioning⁵⁵, and task performance^{58–60}, we also examined between a negative symptom amotivation factor and DDM parameters. This amotivation factor was calculated by applying published factor loadings⁶¹ to avolition/apathy and asociality/anhedonia items on the SANS and summing those to obtain a composite measure.

Gaze perception task

Participants completed a self-referential gaze perception task¹⁶ in which they viewed faces and indicated whether the person was looking at them (Yes-Looking at me) or not (No-Not looking at me) via button press. Stimuli were greyscale face images⁶² depicting different gaze directions (direct, indirect), emotions (neutral, fearful), and head orientations (forward, deviated 30°). Trials consisted of a 1000ms fixation, 100ms blank screen, 100ms stimulus, up to 2000ms response period (terminated following response), and a 600ms inter-trial interval. Trials were presented randomly across four blocks (64 trials per condition x 8 conditions = 512 trials). Block order and response orientation were counterbalanced across participants (*block order* = neutral-fearful-neutral-fearful -or- fearful-neutral-fearful-neutral; *response orientation* = yes-CTRL, no-SHIFT -or- yes-SHIFT, no-CTRL). All participants began with a brief practice to acclimate them to the task. The task was programmed in E-prime 2.0 Professional (Psychology Software Tools,

Inc) and lasted ~20-25 minutes. Non-response trials and trials with invalidly quick responses (< 300ms)⁶³ were removed. Sample stimuli and a task overview are shown in Figure 2.

To index performance, in addition to deriving DDM parameters (discussed below), we also calculated traditional behavioral measures as a point of comparison. These measures included the task-averaged reaction time, accuracy, and proportion of ‘yes-looking at me’ responses.

Figure omitted to comply with policies of preprint server.

Figure 2. Gaze discrimination task. Participants pressed a button to indicate whether the face was looking at them (Yes/No). Faces varied in gaze direction (direct, averted), emotion (neutral, fearful), and head orientation (forward, deviated). ITI = inter-trial interval; ms = milliseconds.

Computational modeling

Overview of DDM

We used hierarchical Bayesian DDM’s³² to characterize the mechanisms of gaze perception in our three groups.

Modeling approach

We undertook an exploratory modeling-building approach to determine a model that best accounted for choices and RTs. We parameterized the DDM to examine how diagnostic group, others’ gaze direction, head orientation, and emotional expression impact the computationally defined processes laid out by the DDM during gaze perception.

1) Model specification. We began with a full model space of 30+ variations of the DDM. Critically, these models differed in their specification of how task conditions (gaze, head orientation, and emotion of stimuli) impacted DDM parameters. This full model space was then refined down to $n = 8$ plausible models, which were subject to additional testing according to recommended guidelines⁶⁴. Details of all models tested and the process by which the model space was refined is described in the supplement. All models were implemented as hierarchical Bayesian models where subject-level fixed effects for all parameters were informed by (diagnostic) group-level means and variances. We used weakly informative priors with a non-centered parameterization (i.e., parameters are sampled in a ‘standard’ space and later scaled/transformed), which can aid in Markov Chain Monte Carlo (MCMC) sampling for complex models.

2) Model implementation. Models were implemented in Stan 2.21.0⁶⁵ on a high-performance computing cluster using RStan 2.21.7 and cmdstanr 0.0.6 (cmdstan 2.32.2). We performed hierarchical Bayesian sampling using Stan’s No-U-Turn sampler (NUTS), an adaptive variant of Hamiltonian Monte Carlo (HMC). HMC-based algorithms like NUTS can converge to high dimensional distributions faster than other popular algorithms (e.g., Gibbs, random walk Metropolis), but—unlike traditional HMC—NUTS requires minimal user input during tuning phases⁶⁶. Model testing and comparison were based on 8,000 post-warmup samples for which diagnostic tests (described below) indicated convergence over multiple chains. After selecting a winning model, a final version was run using 36 chains with 2,500 warm-up samples and 6,000 post-warmup draws per chain, resulting in 216,000 total post-warmup draws. Convergence checks were performed for all model fits. In all cases, these suggested that parameters converged to target distributions: there were no divergences and, for all parameters, R-hat values were < 1.1

⁶⁷, trace plots were well-mixed, and autocorrelation was ~ 0 by a lag of ~ 30 . Finally, parameter recovery was performed on the baseline model using $N=50$ simulated datasets. Results showed good recovery of parameters at the group- (94-98% recovery) and subject-level (94-96% recovery).

3) Model comparison. We performed model comparisons using leave-one-out (LOO) cross-validation ⁶⁸ to determine which model best accounted for the data. We chose a cross-validation approach because it helps avoid over-fitting ⁶⁴. For all groups, the winning model (called “Model 10” here and throughout the supplement) was one in which all parameters varied by diagnostic group and evidence accumulation (drift rate) was influenced by the gaze direction, head orientation, and emotion expression of stimuli. It assumed that response caution (threshold separation), start point (expectancy bias), and NDT operated as trait-level processes that did not vary in response to stimulus changes. This is a reasonable model account of the psychological phenomena because the drift rate is known to be influenced by the physical qualities of the stimulus. This model performed marginally better than one other model (called “Model 9” here and throughout the supplement), which accounted for the effects of stimulus gaze direction and head orientation—but not emotion—on evidence accumulation (drift rate). Complete results of model comparisons using LOO cross-validation is provided in the supplement.

4) Predictive checks. Posterior predictive checks were used to test the accuracy of predicted choices and RT distributions produced by the winning model (Model 10) for all groups and task conditions. We obtained 72,000 posterior samples (i.e., 2,500 warmup draws, 2,000 post-warmup draws, over 36 chains) and used these samples to simulate trial-level choice and RTs for each subject. A description of the simulation process (and associated code) is available in the supplement. Results showed that model-predicted choice proportions and RT distributions

mapped closely onto observed choice proportions and RT distributions for all diagnostic groups and task conditions. The only exception is that the model slightly underpredicted the tails of the RT distribution in cases where few trials ($< 1\%$ of all observations) were available, specifically when predicting the RTs of incorrect response trials in a condition with very high overall accuracy. Together, this indicated that the winning model had high predictive accuracy.

5) Additional data preparation. A preliminary examination of condition effects on DDM group-level parameters indicated that head orientation (specifically the congruency of head orientation with gaze direction), but not facial emotion, credibly influenced drift rates (see supplemental analyses). Therefore, for analysis of group differences (discussed below under ‘Statistical Analyses’), we marginalized drift rates for emotion conditions, meaning we averaged over each posterior sample for fearful and neutral faces within direct-forward, direct-deviated, indirect-forward, and indirect-deviated conditions. Then, for correlations and regression analyses, we separately calculated two measures—overall drift rates and drift bias—separately for forward and deviated heads. Overall drift rates were calculated by flipping the sign of indirect-forward and indirect-deviated samples (which were originally negative-going) and marginalizing over gaze conditions, meaning we averaged over each posterior sample for direct and indirect faces within forward and deviated head conditions. Drift bias was calculated using the same process, but *without* flipping the sign for indirect gaze posterior samples. This provided a measure of the relative magnitude of drift rates for direct and indirect gaze, where a drift bias of 0 indicates a similar evidence accumulation efficiency for direct and indirect gaze; values > 0 indicate greater relative efficiency for direct gaze and, therefore, a perceptual bias toward “looking at me”; and values < 0 indicate greater relative efficiency for indirect gaze and, therefore, a perceptual bias toward “not looking at me”.

Statistical analyses

Analyses were based on parameters from the winning model—Model 10. We performed all analyses in R version 4.1.0 (via RStudio version 1.4.1717)⁶⁹. Before running analyses, to retain as much data as possible, we winsorized the outermost 1% of observations for several measures (all traditional performance measures, drift bias forward/deviated, and antipsychotic dosing) that contained outliers.

Analysis plan

First, we examined between-group and within-group condition differences in DDM parameters. We calculated the 90% highest density intervals (HDI) of the posterior differences between groups and task conditions. We considered a 90% HDI of differences that did *not* contain zero a credible difference. We report 90% HDIs in brackets alongside the means of the difference interval.

Second, we examined potential mechanisms of relationships between gaze perception and general and social cognition found in prior studies. We ran exploratory, uncorrected, zero-order Pearson correlations between DDM parameters, BACS, and MSCEIT in the SZ sub-study sample for which BACS (28 SZ, 18 HC) and MSCEIT were collected (27 SZ, 18 HC). We did the same to explore relationships between DDM parameters, delusions (SAPS-Delusion), hallucinations (SAPS-Hallucination), and negative symptom-related amotivation (SANS-Amotivation) in SZ. Next, we ran follow-up correlations between these external metrics and traditional performance metrics (accuracy, RT, and percentage of ‘yes’ responses) to ascertain whether observed relationships were unique to DDM parameters or also evident through traditional metrics. Finally, because antipsychotics are known to influence RTs, we also tested whether antipsychotic dose was correlated with any performance-derived measures using

chlorpromazine (CPZ) equivalency (calculated with ‘chlorpromazineR’⁷⁰). These were performed using Kendall’s Tau to account for the skewed distribution of CPZ data. All tests were performed using an alpha of $p < .05$ and are reported below with 95% *confidence intervals* for test statistics in brackets (i.e., “CI = [lower, upper]”).

Third, to maximize statistical power we combined data of SZ and HC in the SZ sub-study (27 SZ, 18 HC) and tested whether DDM parameters could predict real-world social functioning (SASSR-Social) dimensionally—after accounting for diagnosis, general cognition (BACS), and social cognition (MSCEIT), all of which are predictors of social functioning^{71–79}. We ran hierarchical linear regressions using the ‘lm’ function in R. After controlling for diagnostic group (SZ=1, HC=0), BACS, and MSCEIT, DDM parameters were added in order of correlation strength with the dependent variable and retained if the full model explained significantly more variance than the reduced model. To determine whether results were robust to antipsychotic effects, we performed a sensitivity analysis on the winning regression model, controlling for antipsychotic dosing before DDM parameters were entered. To determine whether results were specific to DDM parameters, we tested whether traditional accuracy, RT, or proportion of yes responses on the gaze task could also predict unique variance in social functioning above and beyond diagnosis, BACS, and MSCEIT. All tests were, again, performed using an alpha of $p < .05$ and are reported with 95% *confidence intervals* for test statistics.

Results

Sample characteristics are shown in Table 1.

Table 1. Sample Characteristics

HC (N = 34)	BD (N = 38)	SZ (N = 28)
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Variable	<i>n</i>	<i>M</i>	<i>SD</i>	<i>n</i>	<i>M</i>	<i>SD</i>	<i>n</i>	<i>M</i>	<i>SD</i>
Demographics									
Age	34	41.56	12.92	37	41.16	11.51	28	41.61	13.3
Sex (Female) ^a	34	0.38	—	37	0.46	—	28	0.29	—
Education (Years)	32	16.72	2.26	36	15.39	2.36	28	13.54	1.88
Parental Education (Years)	30	14.67	2.75	22	15.55	2.7	28	14.54	3.68
Race									
White ^a	32	0.72	—	36	0.89	—	27	0.67	—
Black/African American ^a	32	0.12	—	36	0.06	—	27	0.26	—
Multiracial ^a	32	0.06	—	36	0.03	—	27	0.04	—
American Indian/Alaska Native ^a	32	0.03	—	36	0.03	—	27	0	—
Asian ^a	32	0.06	—	36	0	—	27	0	—
Hispanic ^a	32	0	—	36	0	—	27	0.04	—
Clinical									
Illness Duration	0	—	—	37	24.32	12.27	28	21.07	12.97
Diagnosis									
Schizophrenia ^a	0	—	—	37	0	—	28	0.75	—
Schizoaffective ^a	0	—	—	37	0	—	28	0.25	—
Bipolar I ^a	0	—	—	37	1	—	28	0	—
Symptoms									
Positive: SAPS-Hallucination	0	—	—	0	—	—	28	5.79	6.64
Positive: SAPS-Delusion	0	—	—	0	—	—	28	8.86	9.58
Negative: SANS-Amotivation	0	—	—	0	—	—	27	0.66	0.52
Negative: SANS-Expressive	0	—	—	0	—	—	27	0.69	0.69
Medication									
CPZeq	34	0	0	33	85	136.4	27	507.8	455.5
General/Social Cognition									
Cognition, General: BACS (z score)	18	0.52	0.44	0	—	—	28	-0.33	0.71
Cognition, Social: MSCEIT (z score)	18	0.47	0.64	0	—	—	27	-0.34	0.7
Gaze Task Performance									
RT (ms)	34	681.5	102.1	38	750.01	143.67	28	807.8	166.6
Accuracy ^a	34	0.83	0.07	38	0.77	0.08	28	0.80	0.09
‘Looking at Me’ Responses ^a	34	0.39	0.10	38	0.43	0.11	28	0.42	0.11
Social Functioning									
Social Functioning: SAS-SR	18	4.2	0.46	0	—	—	27	3.61	0.46

Note. ^a Proportions; RT = reaction time; ms = milliseconds; CPZeq = chlorpromazine equivalent; BACS = Brief Assessment of Cognition in Schizophrenia; MSCEIT = Mayer-Salovey-Caruso Emotional Intelligence Test; SANS = Scale for the Assessment of Negative Symptoms; SAPS = Scale for the Assessment of Positive Symptoms; n = subjects with valid data; M = mean; SD = standard deviation.

Group differences in DDM parameters

Figure 3 plots the posterior estimates of the DDM parameters (panels A-G). We discuss each of these parameters in turn first starting with the parameters that most directly shape the accumulated evidence: drift rate and threshold separation.

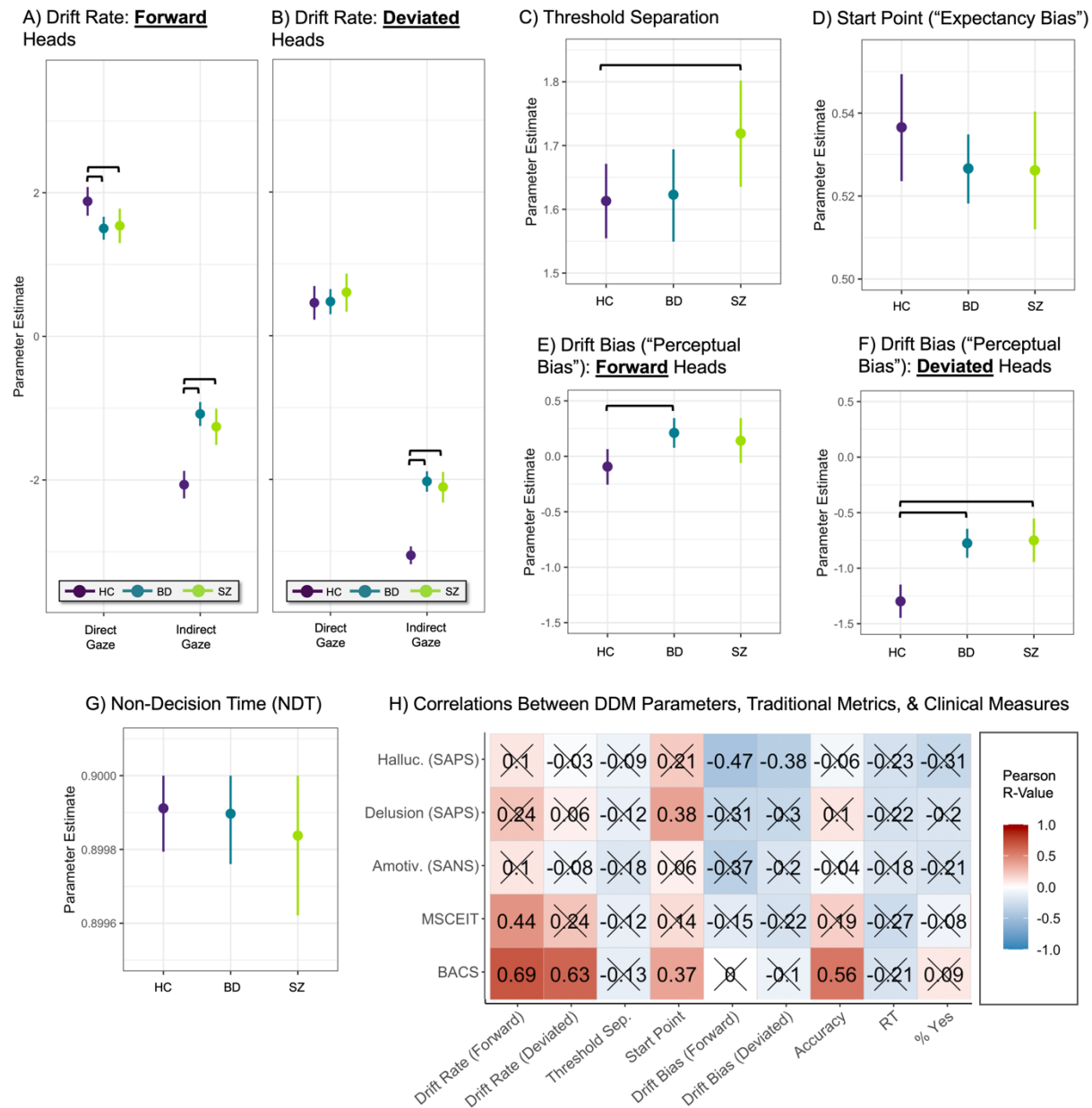


Figure 3. A-G) Group differences in DDM parameters. H) Zero-order correlations between DDM parameters, traditional performance metrics, general/social cognition, and SZ symptoms. For panels A-G: Points and error bars represent the mean and 90% highest density interval (HDI) of group posteriors, respectively. Horizontal black brackets indicate credible differences that do not contain zero. For panel G: Value shown for NDT is a proportion of the minimum RT. For panel H: Values shown are Pearson R values that are significant at $p < .05$

(uncorrected) unless marked with an ‘X’. BACS= brief assessment of cognition in schizophrenia; DDM=drift diffusion model; MSCEIT= Mayer-Salovey-Caruso Emotional Intelligence Test; SANS=scale for the assessment of negative symptoms; SAPS=scale for the assessment of positive symptoms; RT = reaction time; % Yes = proportion of ‘yes-looking at me’ responses.

Drift rates

Recall the best-fitting model allowed the drift rate to vary by the gaze direction, head orientation, and emotional expression of stimuli. Figure 3A plots the drift rate estimates for direct and indirect gaze when the heads faced forward, averaging across the emotional conditions. Figure 3B plots the drift rates for deviated heads. As the choice option of “looking at me” was coded as the top choice threshold and “not looking at me” was coded as the bottom choice threshold, the drift rates should reflect this coding with direct gaze faces having positive drift rates and indirect gaze having negative drift rates.

Overall, the drift rates indicated a general inefficiency of evidence accumulation during gaze perception in patients. This was evidenced by stronger drift rates in HC relative to SZ ($M = 0.49$, $[0.31, 0.67]$) and BD ($M = 0.59$, $[0.45, 0.74]$) when we collapsed across all task conditions. BD and SZ did not differ ($M = -0.11$, $[-0.27, 0.06]$).

Within task conditions, the pattern of results was similar. When gaze was direct and head orientation was forward, HC showed higher drift rates than SZ ($M = 0.34$, $[0.03, 0.65]$) and BD ($M = 0.38$, $[0.12, 0.63]$), while BD and SZ did not differ ($M = -0.04$, $[-0.32, 0.26]$). When gaze was indirect and head orientation was forward, HC showed higher drift rates than SZ ($M = -0.81$, $[-1.13, -0.49]$) and BD ($M = -0.99$, $[-1.24, -0.73]$), while BD and SZ did not differ ($M = 0.18$, $[-$

0.13, 0.48]). When gaze was indirect and head orientation was deviated, HC showed higher drift rates than SZ ($M = -0.95$, $[-1.19, -0.70]$) and BD ($M = -1.03$, $[-1.22, -0.84]$), while BD and SZ did not differ ($M = 0.08$, $[-0.18, 0.33]$). The exception was when gaze was direct and head orientation was deviated, for which all groups showed collectively poor accuracy. In this condition, there were no credible differences between groups in terms of drift rates (HC-SZ: $M = -0.15$, $[-0.51, 0.20]$; HC-BD: $M = -0.02$, $[-0.31, 0.28]$; BD-SZ: $M = -0.13$, $[-0.45, 0.19]$).

Threshold separation

SZ had credibly higher threshold separation than HC (Figure 3C; $M = 0.11$, $[0.21, 0.004]$), while BD did not show credible differences relative to SZ ($M = -0.1$, $[-0.21, 0.02]$) or HC ($M = -0.01$, $[-0.10, 0.09]$). This difference indicates that SZ had greater response caution than HC. This increased threshold separation helped offset the reduction in performance from decreased drift rates and may have been used in SZ as compensatory response caution, preserving accuracy at the expense of even slower RT.

Start point

All three groups had start points biased toward “looking at me” responses (i.e., all start points > 0.5), but there were no credible differences between groups in terms of the start points (Figure 3D; $M = 0.01$, HC-SZ: $[-0.01, 0.03]$; $M = 0.01$, HC-BD: $[-0.01, 0.03]$; BD-SZ: $M = 0.00$, $[-0.03, 0.02]$). This lack of a credible difference suggests that expectancy biases are a normative aspect of gaze perception but not a driver of altered performance in SZ and BD relative to HC.

Drift bias

The DDM captures a second way that participants can be biased in their responses: via an asymmetry between the magnitudes of the drift rates for direct and indirect gazes. To identify

this drift bias, we calculated the relative magnitudes of the drift rates for direct and indirect gaze for each condition (Figure 3E and 3F). BD showed greater drift bias towards “looking at me” responses than HC for forward (HC-BD: $M = -0.30$, $[-0.51, -0.10]$) and deviated heads (HC-BD: $M = -0.523$, $[-0.72, -0.33]$). SZ showed greater drift bias towards “looking at me” for deviated heads (HC-SZ: $[-0.80, -0.31]$, $M = -0.55$), but not forward heads (HC-SZ: $M = -0.23$, $[-0.49, 0.03]$). Drift biases in SZ and BD did not differ (*Forward*: BD-SZ: $M = 0.07$, $[-0.18, 0.31]$; *Deviated*: BD-SZ: $M = -0.03$, $[-0.26, 0.21]$). These differences suggest that the self-referential biases in patients are isolated to disruptions in the evidence accumulation process. The pattern of results for drift biases also showed that head orientation is a predominant cue impacting perceptual biases.

Across all groups, participants showed negligible-to-no drift bias toward ‘looking at me’ for forward heads (*All groups*: $M = 0.09$, $[-0.01, 0.18]$); as noted above, this bias was most evident in BD versus HC) and marked biases toward ‘not looking at me’ for deviated heads (*All groups*: $M = -0.94$, $[-1.04, -0.85]$; though, as noted above, this was less evident in SZ and BD versus HC).

Non-decision time

The groups did not show credible differences in NDT parameters, suggesting comparable time spent on sensory and motor processes (Figure 3G; HC-SZ: $M = 0.0001$, $[-0.0002, 0.0004]$; HC-BD: $M = 0$, $[-0.0002, 0.0002]$; BD-SZ: $M = 0.0001$, $[-0.0002, 0.0004]$).

Relationships between DDM parameters, BACS, MSCEIT, and SZ Symptoms

Figure 3H shows correlations for primary comparisons of interest. The supplement contains complete results for all correlations, including post-hoc tests and sensitivity analyses.

Relationships with BACS and MSCEIT

BACS was correlated with start point ($r = .37$, $CI = [.09, .60]$, $p = .012$) and drift rates in forward ($r = .69$, $CI = [.50, .82]$, $p < .001$) and deviated head conditions ($r = .63$, $CI = [.42, .78]$, $p < .001$), but not threshold separation ($r = -.13$, $CI = [-.41, .16]$, $p = .372$) or drift bias for forward ($r = -.003$, $CI = [-.29, .29]$, $p = .985$) or deviated heads ($r = -.10$, $CI = [-.38, .19]$, $p = .492$). This suggests that those with better general cognitive ability tended to show more efficient evidence accumulation and more biased expectations about gaze being self-directed. Among traditional performance metrics (accuracy, RT, proportion of “yes-looking at me” responses), higher accuracy was related to improved BACS performance ($r = .56$, $CI = [.32, .73]$, $p < .001$), but all other correlations were not significant.

MSCEIT was correlated with drift rate for forward heads ($r = .44$, $CI = [.16, .65]$, $p < .003$), but not deviated heads ($r = .24$, $CI = [-.06, .50]$, $p = .114$), other DDM parameters (all p 's $> .05$), or any of the traditional performance metrics (all p 's $> .05$). This indicates that among forward heads more efficient evidence accumulation was associated with improved emotion-based social cognition.

Post-hoc analyses (reported in the supplement) showed that none of these correlations were significantly correlated with antipsychotic dose and that observed relationships were similar within SZ only. This suggests the observed results were unlikely to be accounted for by antipsychotic dose and/or group differences in these variables.

Relationships with SZ symptoms

Within SZ, SAPS-Delusion scores were correlated with start point parameters (Figure 3H; $r = .38$, $CI = [.01, .66]$, $p = .044$), but not other DDM parameters or traditional metrics (all

p 's < .05), meaning that individuals with more delusional symptoms tended to have more biased expectations about gaze being self-directed. Sensitivity analyses (reported in the supplement) showed that this relationship was strengthened when potentially influential cases were removed.

Within SZ, SAPS-Hallucination scores were correlated with drift bias for forward ($r = -.47$, $CI = [-.72, -.12]$, $p = .011$), and deviated heads ($r = -.39$, $CI = [-.66, -.01]$, $p = .043$), suggesting that individuals with more severe hallucinations were more susceptible to perceptual biases toward “not looking at me” when discriminating eye gaze. Sensitivity analyses (reported in the supplement) showed that, when potentially influential cases were removed, the relationship between hallucination and drift bias for *forward heads* strengthened, but the relationship with drift bias for *deviated heads* was no longer significant. This suggests the former is a more robust finding and, as such, is the only result of these two that we will interpret.

SANS-Amotivation was not significantly correlated with DDM parameters or traditional metrics (all p 's < .05).

Post-hoc analyses (reported in the supplement) showed that these measures were not related to antipsychotic dose. This suggests the observed results were unlikely to be accounted for by antipsychotic effects.

Predicting social functioning in SZ and HC

To understand whether DDM parameters could explain unique variance in real-world social functioning dimensionally (across SZ and HC), above and beyond well-documented predictors (BACS, MSCEIT), we used hierarchical regression analyses. As shown in Table 2, after controlling for diagnosis, BACS, and MSCEIT, start point—but not other DDM parameters—was a significant predictor ($b = -4.84$, $t = -2.31$, $p = .026$) and accounted for 8.2%

of additional variance in real-world social functioning dimensionally across SZ and HC ($R^2 = .397$, $\Delta R^2 = .082$, $\Delta F = 5.33$, $p = .026$). This suggests that individuals who had stronger expectation biases about others looking at them tended to have poorer real-world social functioning.

Post-hoc analyses (reported in the supplement) showed that these results were: unchanged when we controlled for antipsychotic dose, similar when regressions were performed within SZ only, and unique to DDM parameters: traditional performance metrics were unable to predict SAS-SR Social-Leisure scores above and beyond diagnosis, BACS, and MSCEIT.

Table 2. Predicting Social Functioning from Gaze DDM Parameters

Model/Predictor	Model Change Statistics				Predictor Statistics			
	Type	R^2 (ΔR^2)	ΔF	p	b (SE)	95% CI	t	p
<i>Model 1</i>	Linear	0.314 (--)	--	--				
(Intercept)					4.17 (0.13)	[3.91, 4.44]	32.03	< .001***
SZ Diagnosis					-0.56 (0.18)	[-0.93, -0.2]	-3.11	0.003**
BACS					0.07 (0.12)	[-0.18, 0.31]	0.56	0.581
MSCEIT					-0.01 (0.11)	[-0.24, 0.21]	-0.11	0.914
<i>Model 2a^a</i>	Linear	0.328 (0.014)	0.81	0.373				
(Intercept)					4.49 (0.37)	[3.73, 5.24]	12.02	< .001***
SZ Diagnosis					-0.61 (0.19)	[-0.99, -0.23]	-3.22	0.003**
BACS					0.14 (0.14)	[-0.15, 0.43]	0.95	0.347
MSCEIT					-0.01 (0.11)	[-0.23, 0.22]	-0.06	0.95
Drift Rate (Forward)					-0.14 (0.16)	[-0.46, 0.18]	-0.90	0.373
<i>Model 2b^a</i>	Linear	0.342 (0.028)	1.65	0.207				
(Intercept)					4.47 (0.26)	[3.93, 5.01]	16.89	< .001***
SZ Diagnosis					-0.61 (0.18)	[-0.98, -0.24]	-3.32	0.002**
BACS					0.17 (0.14)	[-0.12, 0.46]	1.18	0.245
MSCEIT					-0.04 (0.11)	[-0.27, 0.19]	-0.36	0.719
Drift Rate (Deviated)					-0.26 (0.20)	[-0.66, 0.15]	-1.28	0.207
<i>Model 2c^a</i>	Linear	0.375 (0.060)	3.74	0.060				
(Intercept)					4.36 (0.16)	[4.04, 4.68]	27.38	< .001***
SZ Diagnosis					-0.61 (0.18)	[-0.97, -0.25]	-3.44	0.001**
BACS					0.05 (0.12)	[-0.18, 0.29]	0.45	0.657
MSCEIT					0.01 (0.11)	[-0.21, 0.23]	0.11	0.909
Drift Bias (Deviated)					0.17 (0.09)	[-0.01, 0.35]	1.94	0.060
<i>Model 2d^a</i>	Linear	0.397 (.082)	5.33	0.026*				
(Intercept)					6.75 (1.12)	[4.48, 9.03]	6.01	< .001***
SZ Diagnosis					-0.57 (0.17)	[-0.92, -0.22]	-3.31	0.002**
BACS					0.15 (0.12)	[-0.09, 0.4]	1.28	0.208

MSCEIT					-0.02 (0.11)	[-0.24, 0.19]	-0.22	0.829
Start Point					-4.84 (2.10)	[-9.08, -0.6]	-2.31	0.026*
<i>Model 3a</i> ^b	Linear	0.399 (0.002)	0.11	0.739				
(Intercept)					6.96 (1.30)	[4.34, 9.59]	5.37	< .001***
SZ Diagnosis					-0.57 (0.18)	[-0.92, -0.21]	-3.22	0.003**
BACS					0.16 (0.12)	[-0.09, 0.4]	1.28	0.210
MSCEIT					-0.02 (0.11)	[-0.24, 0.2]	-0.22	0.830
Start Point					-4.92 (2.13)	[-9.24, -0.6]	-2.30	0.027*
Threshold Sep.					-0.1 (0.31)	[-0.72, 0.52]	-0.34	0.739
<i>Model 3a</i> ^b	Linear	0.397 (0.0003)	NA	NA				
(Intercept)					6.72 (1.17)	[4.35, 9.08]	5.75	< .001***
SZ Diagnosis					-0.57 (0.18)	[-0.93, -0.22]	-3.27	0.002**
BACS					0.15 (0.12)	[-0.1, 0.4]	1.21	0.233
MSCEIT					-0.02 (0.11)	[-0.24, 0.2]	-0.19	0.849
Start Point					-4.77 (2.18)	[-9.19, -0.36]	-2.19	0.035*
Drift Bias (Forward)					0.02 (0.15)	[-0.28, 0.32]	0.13	0.895

Note. *** $p < .001$, ** $p < .01$, * $p < .05$. Winning model shaded in gray. NA = improvement was so

negligible that values cannot be calculated. ^a Relative to Model 0. ^b Relative to Model 2d

Discussion

Self-referential gaze perception is a key social cognitive process. This paper used the DDM to delineate the precise decision-making deficits underlying altered performance in SZ and BD previously identified in the literature. Our results indicated that across participants, efficiency of evidence accumulation was influenced by gaze direction, head orientation, and emotion of stimuli. We further uncovered process-level differences in SZ and BD, including less efficient evidence accumulation, perceptual biases predisposing self-referential responses, and greater caution (SZ only).

Patients accumulated evidence less efficiently than HC and, across SZ and HC, more efficient evidence accumulation was related to better general and emotion-based social cognition. This aligns with prior data^{33–36,39,80–82} to suggest that patients' performance alterations across a range of tasks reflect a “general inefficiency” —potentially due to general cognitive deficits³⁹— in the ability to extract information and accumulate it as evidence to make a decision. Crucially,

our results show that these deficits also impact key social cognitive processes like gaze perception. This represents one avenue via which a general processing inefficiency may exert influence on the social lives of patients with SZ and BD. Real-world social interactions require rapid processing of social cues. Inefficient evidence accumulation for such cues may disrupt the natural flow of interaction, by making the individual prone to mistakes and slower processing. Although we did not find relationships between social functioning and evidence accumulation efficiency, this may be a measurement issue; studies should further explore how evidence accumulation impacts functioning dynamically, for example, using observation- or performance-based assessments to examine moment-to-moment social interactions.

As indicated by the start points, all groups showed expectancy biases toward beliefs that others were “looking at me.” This is consistent with nonclinical data showing that our default response is to endorse gaze as self-referential⁸³. Although start points did not vary between groups, they were uniquely related to social functioning and delusions. *First*, across SZ and HC, more self-referential start points predicted poorer social functioning above and beyond diagnosis, general cognition, and emotion-based social cognition. Therefore, aberrant self-referential beliefs indexed by the DDM may capture unique aspects of social functioning, aiding the prediction of functional outcomes. *Second*, within SZ, more self-referential start points were related to more severe delusions. Given that delusions are thought to stem from maladaptive belief-level biases^{50,51}, this points to a viable mechanism that could account for observed links between gaze perception and delusions^{26,28}. These findings echo recent work emphasizing the crucial role that belief-level social cognitive biases play in general social functioning, as well as symptoms in SZ⁸⁴⁻⁸⁷. Although prior work has measured such biases using self-reports⁸⁸ and choice-based

psychophysical measures^{15,24,25,29,89,90}, computational approaches may offer a novel means of measuring biased expectations.

Instead of showing biases at the belief level, patients showed self-referential *perceptual* biases toward “looking at me”, as indicated by drift bias parameters (for deviated heads only in SZ). This perceptual bias raises questions about the design of neuroplasticity-based, computerized social cognitive training, which have often aimed to broadly improve a targeted ability through repeated computerized practice exercises (see examples^{91,92}). If such interventions target processing efficiency generally but not discrepant efficiency for different choice types, biased judgments stemming from perceptual biases will remain unchanged. Instead, individualizing training to target areas of reduced processing efficiency may lead to more noticeable reductions in perception-based biases. Additionally, in SZ, greater perceptual bias toward “*not* looking at me” (forward heads only), indexed by drift bias, was associated with more severe hallucinations. Finding a relationship between perceptual biases and symptoms thought to arise from strong biases influencing perception⁴⁹ is promising, but the direction is unexpected. The directionality is likely the by-product of many complicating factors that cannot be fully parsed in the present study. Although this relationship should be interpreted cautiously until it can be replicated, it raises a key point to be considered in future work. Traditionally, studies have largely examined how aberrant biases at the belief level exert influence on belief formation and perceptual experience to give rise to delusions and hallucinations, respectively. However, in our case, distinguishing biases at the belief and perceptual levels via start point and drift bias revealed differential relationships with separate positive symptom dimensions. Ultimately, there may be value in separating biases evident at different processing levels to better

understand the complex nature of relationships between perceptual decision-making, hallucinations, and delusions.

It is noteworthy that DDM parameters—but *not* traditional performance measures—showed relationships with symptoms and functioning. One may wonder how model parameters can reveal such relationships, while the behavioral data they were derived from did not. This is because, unlike mean accuracy and RT, DDM parameters tap into features of the RT distribution (e.g., tails of distributions inform drift rates) that may carry important information regarding individual differences. Additionally, computational modeling enabled the disentangling of the belief-related bias from perceptual biases, which showed unique relationships with different positive symptom dimensions; these could not be revealed using traditional accuracy-based performance metrics. This carries implications for how social cognition can be decomposed to advance our mechanistic understanding of social cognitive dysfunction in disorders like SZ and BD.

SZ also exhibited credible but modest increases in response caution relative to HC during gaze perception. This, in conjunction with inefficient evidence accumulation, impacted task performance, including slower and biased responding in SZ and slower, biased, and less accurate responding in BD found in previous studies of this data^{16,17,20,21}. For SZ, heightened response caution functioned as a protective factor, offsetting their lower drift rates which in turn preserved their response accuracy at the expense of slower RTs. Past studies that modeled SZ decision processes report mixed findings with greater response caution in SZ in some cases^{34,35} (including one interpretation of⁸⁰), but not others^{33,36,81,93}. This suggests that response caution is highly task-dependent, which is consistent with the cognitive literature that treats response caution as under the control of the participant as a means for controlling how they trade speed for

accuracy. This property of response caution makes it interesting to consider from a clinical viewpoint. In many ways, this mirrors the process of cognitive restructuring in Cognitive-Behavioral Therapy, where patients are taught to slow their thinking and challenge initial perceptions to arrive at a more accurate conclusion. Similar skill building may, therefore, be relevant in the augmentation of altered social perception, though it would come at the cost of slower responses. However, with practice, it is possible that it would become more automatic and natural.

Two additional findings warrant further discussion. First, we did not find group differences in NDT, which is frequently slowed in SZ^{33,34,36,81}. Here, we used a relatively simple detection task, whereas prior studies have used more complex tasks. Because NDT increases with task complexity³⁶, disparate results likely reflect different task demands and complexity. Second, we did not observe relationships between DDM parameters and measures of amotivation-related negative symptoms. This may be due to measurement limitations, including the use of the SANS which has inconsistent psychometric properties⁹⁴, thereby introducing external sources of noise. Additionally, our task did not incorporate consequences for judgment accuracy, as occurs in the real world, meaning it may have been ill-suited to tap into amotivation symptoms in SZ. Future studies should explore these relationships with contemporary negative symptom measures and tasks involving social consequences.

These findings should be interpreted considering several limitations. First, we used a task with a brief stimulus duration and assumed, like prior studies^{95,96}, that evidence was sampled from visual short-term memory (STM) rather than the stimulus itself. Considering what is known about visual STM deficits in SZ, we are unable to say whether diminished evidence accumulation efficiency is due to deficits in the ability to extract information from the stimuli or

its STM representation. Future studies should disentangle these possible contributions. Second, we used dichotomous gaze stimuli (self-directed or not) and studies have shown the importance of including ambiguous stimuli that span from self-directed to averted^{15,25,29,89,90}. Future studies should expand this investigation using psychophysical tasks. Third, jointly characterizing accuracy and RT more fully accounts for the decision process, but it also introduces potential confounds related to reductions in processing speed attributable to antipsychotics. Although we cannot fully rule out medication effects, sensitivity analyses did not suggest that results were attributable to antipsychotic dose.

In summary, this study used DDMs to delineate the processes driving altered self-referential gaze perception in SZ and BD. Results revealed that diminished evidence accumulation and perceptual biases may underlie altered gaze perception in SZ and BD and that SZ may engage in compensatory response caution to preserve the accuracy of judgments at the expense of even slower RT. DDM parameters were related to popular measures of general and social cognition, positive symptoms in SZ, and social functioning across SZ and HC. Computational cognitive modeling can, therefore, provide a more nuanced understanding of the mechanisms of social cognitive difficulties, and how those relate to cognition, symptoms, and functioning in the study of psychopathology.

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