Modeling perception and behavior in individuals at clinical high risk for psychosis: support for the predictive processing framework

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Abstract

Early intervention in psychotic spectrum disorders is critical for maximizing key clinical outcomes. While there is some evidence for the utility of intervention during the prodromal phase of the illness, efficacy of interventions is difficult to assess without appropriate risk stratification. This will require biomarkers that robustly help to identify risk level and are also relatively easy to obtain. Recent work highlights the utility of behavioral tasks in understanding the pathophysiology of psychotic symptoms. Computational modeling of performance on such tasks may be particularly useful because they explicitly and formally link performance and symptom expression. Several recent studies have successfully applied principles of Bayesian inference to understanding the computational underpinnings of hallucinations. Within this framework, hallucinations are seen as arising from an over-weighting of prior beliefs relative to sensory evidence. This view is supported by recently-published data from two tasks: the Conditioned Hallucinations (CH) task, which determines the degree to which participants use expectations in detecting a target tone; and a Sine-Vocoded Speech (SVS) task, in which participants can use prior exposure to speech samples to inform their understanding of degraded speech stimuli. We administered both of these tasks to two samples of participants at clinical high risk for psychosis (CHR; N = 19) and healthy controls (HC; N = 17). CHR participants reported both more conditioned hallucinations and more pre-training SVS detection. In addition, there was a significant correlation between participants' performance on both tasks. On computational modeling of behavior on the CH task, CHR participants demonstrate significantly poorer recognition of task volatility as well as a trend toward higher weighting of priors. This latter effect was found to predict performance on both tasks. Taken together, these results support the assertion that these two tasks may be driven by similar latent factors in perceptual inference, and highlight the potential utility of computationally-based tasks in identifying risk.

Introduction

Early detection and treatment of psychosis is critical for maintaining functionality and maximizing clinical outcomes (Kane et al., 2016; Srihari et al., 2014, 2012). This effort has been made more reliable with the systematization of clinical evaluations for psychosis as it develops from the prodromal phase of the illness (Miller et al., 2002; Woods et al., 2014, 2009). Evaluation of progression continues to rely on symptom reports and clinical assessment. However, only a minority of those at clinical high risk of psychosis (CHR) will convert to frank psychosis (Hartmann et al., 2016) and the use of clinical measures alone, while promising, is nonetheless limited in predicting course and triggering treatment initiation (Cannon et al., 2016; Carrion et al., 2016). Development of objective measures for psychotic symptoms and disease states will be critical in identifying psychosis emergence, treating early in the disease trajectory, and maximizing functionality in those affected.

Behavioral measures purporting to assess the cognitive and neural drivers of symptom expression may be sensitive and convenient measures of risk. Behavior on a number of tasks has thus far been linked to severity of specific psychotic symptoms, including hallucinations (Alderson-Day et al., 2017; Cassidy et al., 2018; Powers et al., 2017; Teufel et al., 2015), delusions (Corlett et al., 2007; Corlett and Fletcher, 2012), and positive, (Roiser et al., 2013, 2009; Schmidt et al., 2017), disorganization (Silverstein et al., 2013; Silverstein and Keane, 2011; Uhlhaas et al., 2006), and negative symptoms (Gold et al., 2012; Heerey et al., 2007; Treadway et al., 2009) more broadly.

Measures derived from generative computational models linking behavior and symptom expression may hold particular promise as objective markers for psychiatric disease, in part because such models are capable of describing normal and pathological information processing within a common framework, capturing biology, behavior, and their pathology simultaneously (Browning et al., n.d.; Corlett and Fletcher, n.d.; Friston et al., 2014; Stephan and Mathys, 2014; Wang and Krystal, 2014). Here we utilize a predictive processing framework (Friston et al., 2006; K. Friston, 2005; Friston and Kiebel, 2009), which conceives of perception as the process of unconscious inference, in which we actively infer what is around us by combining our sensory input with our prior beliefs about the world (Friston, 2009). Within this framework, the brain functions as a predictive machine, predicting future states of the world using prior beliefs, which are then integrated with incoming sensory evidence to give rise to conscious perception.

Recent work has highlighted the utility of this predictive processing framework for understanding how specific alterations in learning and inference may produce the positive symptoms of psychosis (Adams et al., 2013b; Corlett et al., 2019, 2010, 2007; K. J. Friston, 2005; Powers et al., 2016; Sterzer et al., 2018). This has been especially true of hallucinations, which have been proposed to arise from inappropriate over-weighting of prior beliefs in perception (Corlett et al., 2019; Powers et al., 2016). Over several years, using multiple different methods, hallucinations have been related specifically to behavior signaling overly-precise priors (Alderson-Day et al., 2017; Cassidy et al., 2018; Powers et al., 2017; Zarkali et al., 2019). This appears to be true in hallucinations within the context of psychotic illness (Cassidy et al., 2018; Powers et al., 2017; Teufel et al., 2015) as well as in the general population (Alderson-Day et al., 2017; Powers et al., 2017), and within hallucinations arising from other neuropsychiatric disorders (Zarkali et al., 2019).

The utility of these behavioral measures as biomarkers may depend upon several as-yet-unknown factors. One such factor is theoretical: within the massive processing hierarchy of the brain, to what degree are these tasks and measures actually measuring the same latent construct? If the proposed abnormalities driving hallucinations (i.e., overly precise priors) are not unitary, the clinical utility of estimating them may be limited. Second, it is unclear whether hyper-precise priors are present not only in fully-formed hallucinations, but also in the earliest phases of illness. If not, the use of such measures to detect abnormalities leading to the expression of frank hallucinations may also be limited.

We present data derived from two tasks purporting to measure hyper-precise priors in hallucinations, collected in an overlapping sample of individuals across two CHR clinic sites, and among and age-matched healthy controls. We demonstrate that both methods are sufficiently sensitive to detect hyper-precise priors in CHR and that their scores are correlated, supporting the hypothesis that these two methods measure the same underlying construct. Lastly, we propose other computational parameters that may signal the need for care and increased risk for conversion in this high-risk group.

Methods

Participants

The sample comprised 19 CHR participants and 17 healthy controls (HC) recruited across two sites: the Georgia Psychiatric Risk Evaluation Program (G-PREP; directed by author G.P. Strauss) (CHR N = 9, HC N = 10) and the Adolescent Development and Preventive Treatment program (ADAPT; directed by author Vijay Mittal) (CHR N = 10, HC N = 7).

Similar recruitment procedures were followed across both sites, which involved referrals of youth displaying early signs of psychosis from local clinicians (e.g., psychiatrists, psychologists, social workers, school psychiatrists) to receive diagnostic assessment and monitoring evaluations. CHR youth were also recruited via online and print advertisements, and in-person presentations to community mental health centers.

Clinical Procedures

The Structured Interview for Psychosis-Risk Syndromes (SIPS) (Miller et al., 1999) was administered to detect the presence of a psychosis-risk syndrome in three possible ways: 1) the presence of attenuated positive symptoms or fully psychotic positive symptoms occurring over a very brief time period; and/or 2) decline in global functioning accompanying the presence of schizotypal personality disorder and age <19; and/or 3) a family history of schizophrenia with decline in functioning. The SIPS contains an instrument, the Scale of Prodromal Symptoms (SOPS), that rates the severity of relevant symptoms along a 7-point scale ranging from absent to severe and psychotic. Ratings in the range of 3 to 5 are required for designation as at CHR. This measure gauges several distinct categories of prodromal symptom domains including positive (unusual thoughts, suspiciousness, grandiosity, perceptual abnormalities, disorganized communication) and negative dimensions (social anhedonia, avolition, expression of emotion, experience of emotions and self, ideational richness, occupational functioning). The Structured Clinical Interview for the Diagnostic and Statistical Manual (SCID-I) (First et al., 1995) was administered to determine the presence of psychosis and substance dependence exclusionary criteria. Clinical interviews were conducted in person by advanced doctoral students, trained over a two-month period, and certified to perform the SIPS. All interviewers had inter-rater reliability scores that exceeded the minimum study criterion of Kappa > 80.

Social functioning was assessed with the Global Functioning Scale: Social (GFS-S) (Carrión et al., 2019). This inventory provides ratings of functioning on a 10-point Likert scale where a score of 10 reflects "Superior Social/Interpersonal Functioning" and 1 indicates "Extreme Social Isolation". The scale was designed for adolescents and has been found to be valid and reliable in assessing at-risk populations.

Healthy control (HC) participants were recruited from the local community using posted flyers and electronic advertisements. HC participants had no current major (former Axis I) DSM-5 diagnoses as established by the SCID (First, 2016). HC also had no family history of psychosis and were not taking psychotropic medications. All participants were free from lifetime neurological disease.

All participants provided written informed consent for a protocol approved by the University of Georgia and Northwestern University Institutional Review Boards and received monetary compensation for their participation.

Task Procedures

Tasks were administered on Dell G3 15 gaming Laptops running Windows 10, MATLAB 2018b (www.mathworks.com), and the third iteration of the Psychophysics toolbox (http://psychtoolbox.org/). Responses were made by key press.

Figure 1 provides a schematic of the Conditioned Hallucinations (**Fig. 1a,b**) and the Sine Wave Speech (**Fig. 1c**) tasks.

Conditioned Hallucinations Task

The Conditioned Hallucinations task (Powers et al., 2017) is an auditory detection task. Participants work to detect a tone (1 kHz) embedded in 70-dB SPL white noise and presented concurrently with a flashed gray checkerboard on a black background (**Fig. 1a**). Participants completed a short practice session reporting auditory detection, which was repeated until their responses were at 85% accuracy. Individual threshold (75% detection rate) is determined prior to the start of the experiment proper using the QUEST maximum likelihood-based procedure for threshold determination (Watson and Pelli, 1983), which is part of the Psychtoolbox 3.0 package in MATLAB. Thresholding was performed using two 40-trial interleaved staircases with step-sizes computed by QUEST during the participant responses. A psychometric function was fitted to the QUEST-computed 75% likelihood of detection of target stimulus embedded in noise (reported as dBSNR) (Treutwein and Strasburger, 1999), computing 50% and 25% detection-likelihood tone intensities (**Fig. 1b, left**). Total trial length during thresholding was 2500ms.

In the experiment blocks, participants learned the association between the target auditory stimulus (tone) and a simultaneously presented visual stimulus (checkerboard). After this association-training, the participants were tested on this association over 12 blocks, with 30 trials each. The likelihood of tone presentation at threshold was decreased non-linearly over the 12 blocks, while increasing the presentation of subthreshold and no-tone trials (**Fig1b, right**). The trials were pseudorandomized within each block.

In addition to responding ‘Yes’ or ‘No’ to indicate whether or not they heard the tone, participants also reported their confidence level for their answer choice, by holding the response-button down; holding the button down longer indicated higher confidence in their decision of ‘Yes’ or ‘No’.

Throughout the experiment,a white visual fixation cross was present on a black background. The visual stimulus was a 4x7 gray-on-black checkerboard pattern, with gray squares at 25% brightness to maximize visual stimulation and minimize after-effect. The auditory stimulus was presented via Sony Professional MDR-7056 headphones, and consisted of a 1-kHz pure tone with a 100-ms tapered envelope to prevent transient effects.

For all parts of the experiment, there was a 500- to 1000-ms fixation from trial start, which was followed by the simultaneous presentation of the visual stimulus, and if present, the target auditory stimulus, for one second. Participant responses were recorded for 1000 to 1500ms after stimulus offset. For the main part of the experiment, there was an additional 2000-ms period to record confidence-rating response, during which participants could hold down the response button to indicate their confidence level.

For both detection and confidence responses, if a response couldn’t be reported, the trial was ignored and the stimulus intensity was repeated in the next trial. Figure 1A shows specific stimulus characteristics described here, as well as the structure of a single trial. See Figure 1A for a depiction of stimulus characteristics and trial structure.

Sine-Vocoded Speech Task

Previous work using Sine Wave Speech (SWS) indicates that individuals that hallucinate are more likely to identify an ambiguous auditory stimulus as speech (Alderson-Day, Lima e al., 2017). Sine wave speech (SWS) is typically made by replacing the first three formants (main bands of energy) in speech with pure tones (Remez et al., 1981). It is often unintelligible on first exposure and may not even be recognized as speech-like (often sounding like ‘aliens’ or birdsong). Once the listener knows that it is potentially intelligible as speech (by training via exposure to pre-degradation speech templates, which thus serves as a prior expectation), relatively high levels of comprehension are achieved. Individuals who hallucinate are able to perceive speech in SWS even before exposure to the pre-degradation speech template and without being told speech is present (Alderson-Day, Lima et al. 2017), consistent with the presence of a strong prior for speech in people who hear voices.

Here, we used a similar signal manipulation, sine-vocoded speech (SVS) (Souza & Rosen, 2009), that differs only in the respect that rather than tracking only the first three formants, sine waves are synthesised at the centre frequency of a bank of filters spanning a broad frequency range. With training, SVS sentences can be rendered intelligible and recognised as speech. SVS can also be rendered fully unintelligible by flipping the frequency mapping of the original sentence – providing an ideal control stimulus, with equal complexity (for full details on stimulus production, see Supplementary Materials) **(Fig1c)**.

The “naïve” listening procedure can be challenging to reproduce due to the need to obscure the purpose of the task in advance. Here we therefore deployed a simpler paradigm assessing the ability of CHR participants to discriminate potentially intelligible SVS from unintelligible control SVS (45 trials/condition) before and after exposure to pre-degradation speech templates (i.e. updating their prior expectation). Participants were asked to report whether or not they detected speech on each trial **(Fig1d)**.

In a pre-training phase, participants were presented with intelligible and unintelligible SVS and the number of correctly detected speech trials was recorded (hits) along with the number of unintelligible trials incorrectly classified as speech (false alarms). Following exposure to 90 trials (45 of each stimulus type), participants heard the 45 clear speech templates of the potentially intelligible SVS speech trials, before being tested on their SVS classification again.

Data Analysis

Conditioned Hallucinations Task

We recorded: 1) participant responses for tone detection, 2) response times, 3) confidence rating levels. Trials with no recorded responses were discarded for the purposes of subsequent analyses. Detection probability was computed as the ratio of trials during which participants reported ‘Yes’ for hearing the tone, to those trials during which they reported ‘No’. No-tone trials where the participants recorded a ‘Yes’ response were considered conditioned hallucinations.

The Hierarchical Gaussian Filter (HGF) was fit to the behavioral data from the CH task. This model has been previously optimized specifically for use in the CH task, drawing upon evidence from simulations and Bayesian model comparison (Powers et al., 2017). The model is included in a freely-available toolbox (http://www.translationalneuromodeling.org/hgftoolbox-v4-10/). Details on the model are included in the Supplement.

Between group differences for behavioral, as well as modeling variables were computed using Welch’s two-sample t-test. Correlations between measures were computed using Pearson's product-moment correlation test. All analyses were done using packages *stats*, *tidyverse*, *tableone,* and plots were created using the *ggplot2* package, performed with the software RStudio 1.2.5001 (http://www.rstudio.com/).

Sine Vocoded Speech Task

We recorded the participants' responses for speech detection during both pre-training and post-training blocks. Using signal detection theory ([Stanislaw & Todorov, 1999](#)), we calculated participants' discrimination performance (d'), as well as their bias in classifying speech and non-speech (beta), and how those variables changed following the experience of template stimuli. One indication of enhanced speech priors is the detection of speech in unintelligible speech stimuli: a pre-training bias for speech. Another (following Teufel et al (2015)) is any enhanced benefit of top-down information following template exposure, in the CHR relative to controls.

Results

Sample Characteristics

Table 1 summarizes the demographic features of the full healthy control (N = 17) and CHR (N = 19) samples. The groups were well-matched demographically, with the exception of a significant difference in racial makeup (□^{2} = 13.814 ; p = 0.032). Clinical measures on the CHR and HC groups differed predictably. The CHR group had significantly higher P4 (SIPS Hallucinatory Behavior; T = 9.97, p < 0.001) and lower GAF scores (T =-7.90 ; p < 0.001) compared to matched healthy controls.

Subsets consisting of individuals who performed the CH task (**Table S1**), the SVS task (**Table S2**), and both (**Table S3**) exhibited similar patterns of similarities and differences. CHR youth did not meet lifetime criteria for a DSM-5 psychotic disorder as determined via SCID interview (First et al., 1995). No CHR participants had been prescribed an antipsychotic.

Performance on both tasks differs between groups

As seen in **Figure 2a**, CHR participants were more likely to report conditioned hallucinations (mean = 0.145; $T_{15.5}$ = 2.74; p = 0.015) than matched healthy controls (CH mean = 0.018).

Groups did not differ in initial threshold estimates ($T_{21.99}$; p = 0.098; **Fig. S1a**). This was true only of the conditioned hallucination (no-tone) condition (**Fig. S1b**): group means did not differ at the 75% Detection (CHR mean: 0.88; HC mean: 0.89; $T_{19.9}$ = 0.086; p = 0.93) or 50% Detection conditions (CHR mean: 0.71; HC mean: 0.73; $T_{21.9}$ = 0.78). The group difference in reporting detection at the 25% Detection condition trended toward significance (CHR mean: 0.40; HC mean: 0.30; $T_{21.9}$ = 1.51; p = 0.14).

CHR participants were also more likely to exhibit pre-training detection of sine-wave speech than healthy controls (CHR mean = 0.302; HC mean = mean = 0.012; $T_{14.5}$ = 2.33; p = 0.035; **Fig 2b**).

The behavioral effects for the SVS task reported above could be driven by differences between groups in latent variables, estimated using the Signal Detection Theory approach. During the pre-training portion of the task, the CHR group showed a higher mean bias for classifying the stimuli as speech, even though this difference did not reach significance (T_{30} = 1.65, p = 0.11). Measures of sensitivity did not change significantly after training (main effect of time: $F_{1,30}$ = 2.81 ; p = 0.104; group x time interaction: $F_{1,30}$ = 0.66; p = 0.42). There was a main effect of training ($F_{1,30}$ = 4.44, p = 0.044) and an interaction of group and training ($F_{1,30}$ = 5.33, p = 0.028) in pro-speech bias, with healthy controls exhibiting significantly more pro-speech bias after training (**Fig. S2**).

Furthermore, both the pre-training speech bias (r = -0.513621 , p = 0.017) and the change in speech bias after the training (r = -0.66, p = 0.0019) were significantly correlated with P4 (SIPS Hallucinatory Behavior) score. However, only the pre-post change in speech bias remained significant using an outlier-resistant correlation method (Spearman's rho = -0.75, p < 0.001).

Lastly, performance on both tasks correlated significantly (**Fig. 2c**; Pearson's R = 0.67; T_{21} = 4.1483; p = 4.56 x 10^{-4}) but did not survive application of an outlier-resistant method (Spearman's rho: 0.19, p = 0.3758)

Interestingly, there was no correlation between P4 (SIPS Hallucinatory Behavior) score and either the probability of reporting conditioned hallucinations (R = 0.178; p = 0.54) or pre-training detection of sine wave speech (R = 0.20; p = 0.39).

CHR participants differ in recognition of volatility in stimulus contingencies

To provide further insight into the mechanisms driving the main behavioral effects above, we estimated parameters of a three-level Hierarchical Gaussian Filter (HGF; **Fig. 3a**) (Mathys et al., 2011; Stephan and Mathys, 2014) using behavior from the Conditioned Hallucinations task (Powers et al., 2017).

No difference in decision noise was seen between groups (**Fig. 3f**). CHR participants exhibited a trend toward higher relative precision of priors compared to healthy controls (**Fig. 3e**; T = 1.5821 ; p = 0.132. Similar trends were exhibited in terms of group belief trajectories: CHR participants tended to exhibit more tenacious beliefs that the tone was present when the visual stimulus was on any given trial (**Fig. 3d**) and across the experiment (**Fig. 3c**), although neither of these differences reached statistical significance.

By contrast, groups did differ significantly in their ability to recognize the changing probabilistic relationship between the tone and the visual stimulus (**Fig. 3b**). While HC participants were likely to recognize that the visual stimulus became less predictive of the tone over time, CHR participants did not ($F_{11,242}$ = 3.13; p = 5.78 x 10^{-4}).

Prior precision correlates with performance on both tasks

In order to determine whether prior precision drives performance, we tested for a correlation between HGF-derived prior precision and performance on both tasks. As expected, estimated prior precision predicted performance on the Conditioned Hallucinations task (**Fig. 4a;** $R = 0.871$; $T_{21} = 8.126$; $p = 6.407 \times 10^{-8}$). It also significantly predicted pre-training detection on the SVS task (**Fig. 4b;** $R = 0.753$; $T_{21} = 5.245$; $p = 3.364 \times 10^{-5}$), although this did not survive after removal of outliers.

Discussion

We have demonstrated that participants at CHR for psychosis perform differently on two tasks grounded in predictive processing theory compared to healthy controls: CHR participants exhibited behavior consistent with hyper-precise priors on both tasks. Further, we have shown that performance on the two tasks are correlated, supporting some commonality of mechanism. Modeling of behavior on the Conditioned Hallucinations task using the HGF demonstrated group differences in volatility-related parameter estimates as well as a correlation between prior weighting and performance on both tasks.

The fact that CHR participants exhibited an increased tendency toward conditioned hallucinations as well as pre-training detection of sine wave speech indicates a tendency to exhibit hyper-precise priors even in the earliest phases of the illness. This is consistent with performance of at-risk individuals on recognition of previously-viewed visual scenes (Teufel et al., 2015). Interestingly, modeling of performance in the CHR group reflected that of individuals with psychosis and hallucinations in past work (Powers et al., 2017). Thus, model parameters demonstrated low change in X1, high relative prior precision, and low tendency to appropriately recognize volatility in the A-V contingency, although not all of these differences reached statistical significance. This is consistent with the idea that the CHR condition may be accurately described as both an at-risk state and a syndrome conferring a need for care (Woods et al., 2001).

In the Conditioned Hallucinations task, participants are progressively exposed to fewer and fewer trials in which the target tone is predicted by the presence of the light. Thus, the contingency between the light and tone becomes progressively more volatile over the course of the experiment. Modeling of behavior using the HGF takes this volatility into account, explicitly estimating volatility beliefs related to the inter-stimulus contingency. It is particularly notable that inter-group differences in volatility estimates were even more significant than seen in individuals with fully-formed psychosis (Powers et al., 2017). The behavioral differences between groups in the SVS task shows that while the CHR group has a higher speech-bias before the training, the HC group shows the ability to modulate speech-bias after acquiring new information in the post-training speech detection task, suggesting that the HC participants might have a more robust ability to modulate bias depending on environmental conditions compared to the CHR group. The results from both tasks are broadly consistent with recent accounts of volatility beliefs impacting low-level learning of action-outcome contingencies specifically in psychosis-spectrum illness (Deserno et al., 2020).

If computationally-oriented tasks are meant to assay the same underlying state in the same participants, and if this state is stable over time, performance on these tasks should correlate. This is exactly what we demonstrate. For the first time, two tasks that have been thought to estimate the propensity of participants to rely upon their priors have been run on the same participants. Results show that this property appears to be conserved across tasks. Especially promising is the fact that estimated prior weighting on one task (CH) predicts performance on a separate task meant to assay the same underlying computational parameter. Given that these are only two among several tasks to recently show prior-weighting effects in psychosis and psychosis-related states (Alderson-Day et al., 2017; Cassidy et al., 2018; Powers et al., 2017; Zarkali et al., 2019), it prompts the question as to whether all such measures capture the same latent state. Recent work has highlighted the need to take into account the hierarchical structure inherent in the systems involved (Corlett et al., 2019). Additionally, other models take explicit account of systems involved in action as they relate to perceptual inference (Adams et al., 2013a). Two such recent studies highlight the possibility that inference about action state (i.e., talking vs listening) may be a critical component of hallucinogenesis (Benrimoh et al., 2019, 2018). It remains unclear whether and how tasks that purport to measure these computational alterations may themselves relate to the findings here. Future work should engage participants in a range of tasks meant to assay related model parameters, as well as subject data to several competing models, using principled means of comparison to determine the best explanatory fit for the data observed (Rosa et al., 2010).

The lack of correlation between symptom measures and performance on either tasks stands in stark contrast to the studies this work was based upon (Alderson-Day et al., 2017; Powers et al., 2017), which highlight a specific relationship to hallucinatory propensity in clinical and non-clinical voice-hearers. This lack of observed relationship may be due to several factors. First, there are statistical considerations: sample sizes from this study are approximately half those employed in the original studies, and only a small subset of individuals had self-reported hallucination severity measures; the range of symptom scores observed here is markedly low (P4 scores were clustered around 3 with low variation in the sample); and P4 values fail to take into account several phenomenological factors like frequency, intensity, or loudness of voice-hearing, instead focusing on more clinically-relevant factors such as distress or impairment associated with these experiences. Furthermore, the P4 measure does not take into account the sensory modality of the phenomenological experience, and whether the experience is visual or auditory could be important for mediating the performance on the auditory CH and SVS tasks.However, a second possibility may hold more promise for explaining pathological states leading to hallucinations. In this account, a lack of correlation with symptoms may be related to the phenomenologically semi-developed nature of the voice-hearing experience in CHR: most individuals with non-zero P4 scores experience relatively mild hallucinations, and most are non-verbal (Niles et al., 2019). This relative developmental nascency may mean that those who exhibit altered performance on these tasks and hyper-precise priors may not be individuals with high hallucination propensity at the moment, but may be more likely to develop frank hallucinations in the future. Longitudinal assessment of the relationship between prior precision and hallucinogenesis in CHR as well as symptomatic fluctuation in fully-formed psychosis is warranted to understand the clinical utility of the measures employed here. Further, larger multisite consortiums such as Computerized Assessment for Psychosis Risk (CAPR) and the Psychosis Risk Outcome Network (ProNET) will be important for providing the statistical power, and long-term clinical visit frequency density, necessary for model confirmation and refinement.

Taken as a whole, the findings presented here speak to the potential clinical utility and sensitivity of well-chosen behavioral measures, and--in particular--measures that are based solidly in explicit, formalized generative models for symptom expression. As a field, Computational Psychiatry comprises advocates for data-driven, machine-learning-based approaches to understanding heterogeneity of psychiatric presentation as well as others who espouse modeling as a way to uncover latent processes driving psychopathology (Browning et al., n.d.). The results here represent a way forward that marries the two approaches: employing measures that can be easily gathered from large, heterogeneous samples that nonetheless are able to speak to latent computational states that confer risk for symptom and disease progression. Future attempts may employ larger samples, with measures tied to other symptom domains, in an attempt to meaningfully parse the diversity of this markedly heterogeneous population. It may also be possible to employ both inferential and data-driven approaches within a hierarchical Bayesian framework, as has been done in model-based neuroimaging and electrophysiological approaches (Yao et al., 2018).

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Figure Legends

Figure 1. Behavioral Tasks. The Conditioned Hallucinations (CH) task (**a,b**) and the Sine Wave Speech task (**c,d**) were administered. **a.** In the CH task, participants were asked to detect the presence of a 1-kHz tone embedded in white noise. The tone, when present, was paired with a white checkerboard flash on a black background, causing participants to build an association between the difficult-to-hear tone and salient checkerboard flash. **b.** We estimated individual psychometric curves for tone detection (left) and then systematically varied stimulus intensity over 12 blocks of 30 conditioning trials. Threshold tones were more likely early, and sub-threshold and absent tones were more likely later (right). **c.** Stimuli for the SVS task were created, of which some can become intelligible with training (top), and some are fully unintelligible (bottom). **d.** First participants are naive to the stimuli, and are asked to report their detection of speech for each trial. After training with the pre-degradation speech stimuli, participants repeat the task and are again asked to report their detection of speech.

Figure 2. Group-Level Behavioral Effects a. Mean between-group differences in CH task performance. CHR N= 12; HC N=12. . **b.** Mean between-group differences in SVS task performance. CHR N= 15; HC N=19. **c.** Correlation between SVS task performance and CH task performance. CHR N= 11; HC N=12. $p<0.001$. Asterisk denotes $p < 0.05$.

Figure 3. HGF model analysis. a. Schematic of the computation for the HGF model, mapping experimental stimuli to recorded responses. The first level (X1) represents whether the subject believes a tone was present or not on trial *t*. The second level (X2) is their belief that visual cues are associated with tones. The third level (X3) is their belief about the volatility of the second level. The HGF allows for individual variability in weighting between sensory evidence and perceptual beliefs (parameter *v*). **b.** At X3, there was a significant block-by-group interaction. ***$P < 0.001$. **c-e.** CHR participants also exhibited trends toward higher beliefs in trial-wise (**c**) and experiment-long (**d**) contingencies between the presence of the tone and the visual stimulus. **f.** There were no inter-group effects of decision noise. Error bars represent ±1 SEM. Line shadings represent 95% confidence intervals. Red = CHR; White with black outline = HC.

Figure 4. Relationships between prior precision and performance on both tasks. As expected, performance on the CH task (**a**) was predicted by prior precision. Performance on the separate Sine Wave Speech task (**b**) was driven by estimated prior precision on the CH task.

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Table(s)

Tables

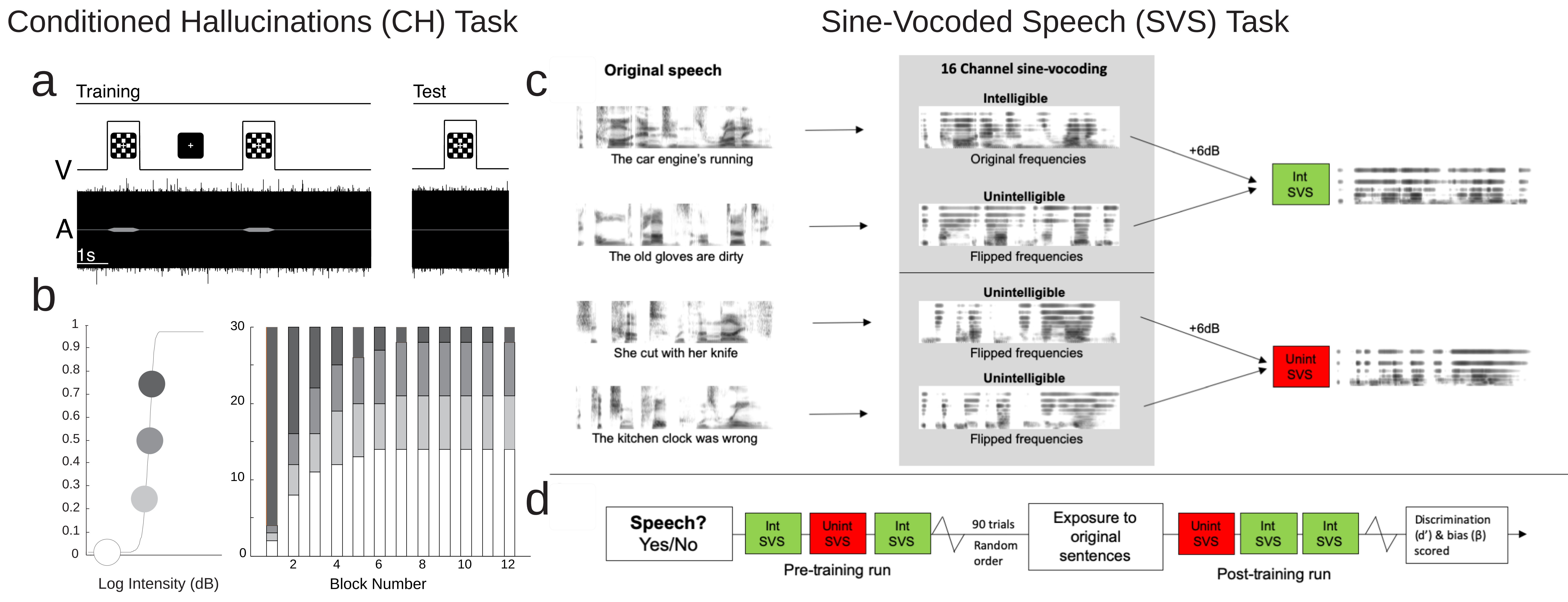
Table 1. Group Demographic Characteristics

	CHR	HC	p
n	19	17	
Age (mean (SD))	20.95 (1.93)	20.88 (1.50)	0.911
Gender (portion male) (%)	5 (26.3)	1 (5.9)	0.232
Race (%)			0.065
African American	4 (21.1)	2 (11.8)	
Asian American	1 (5.3)	6 (35.3)	
Caucasian	12 (63.2)	5 (29.4)	
Latinx	2 (10.5)	1 (5.9)	
Multiracial	0 (0.0)	2 (11.8)	
Native American	0 (0.0)	1 (5.9)	
GAF Score (mean (SD))[a]	60.33 (11.08)	88.60 (5.46)	**<0.001**
WTAR/WRAT Score (mean (SD))[a]	106.78 (12.39)	112.88 (10.94)	0.14
LSHS Total Score (mean (SD))[b]	20.78 (8.29)	4.40 (6.02)	**0.002**
SIPS Positive Symptoms (mean (SD))[b]	12.11 (3.41)	0.29 (0.76)	**<0.001**

SIPS Negative Symptoms (mean (SD))[b]	5.33 (5.72)	1.14 (1.46)	0.071

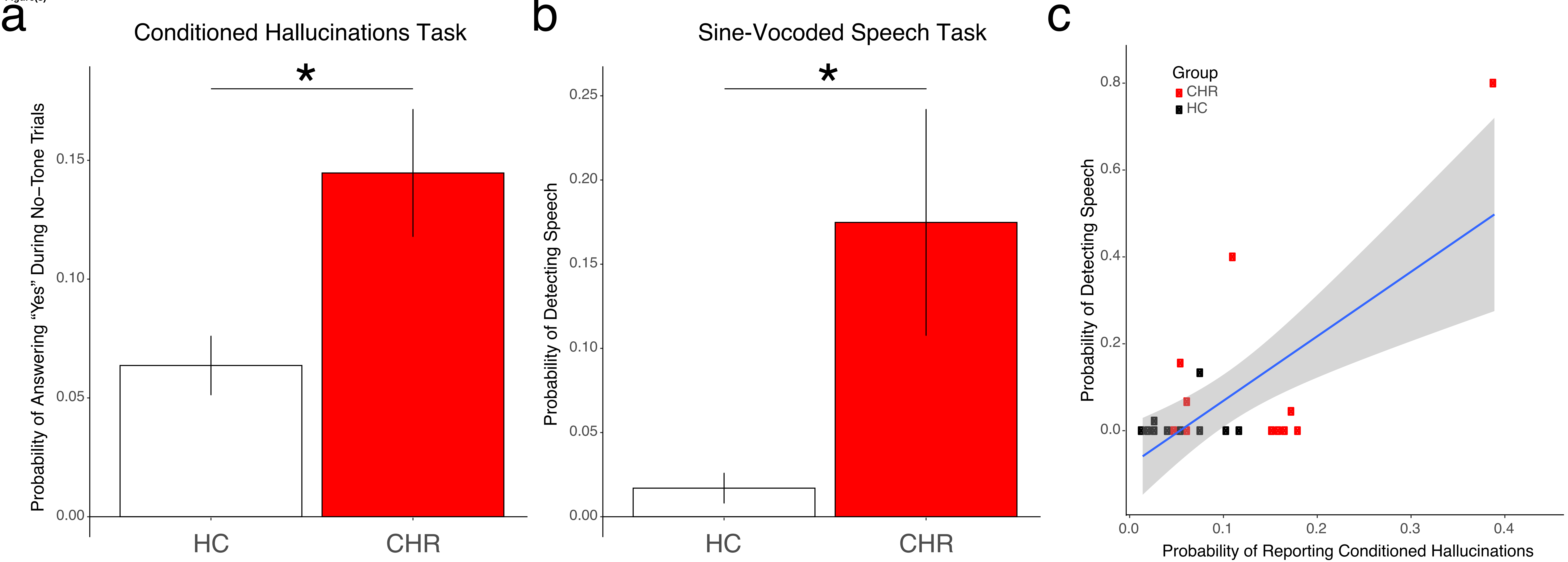
a. CHR N = 18; HC N = 5
b. CHR N = 18; HC N = 7

Figure(s)

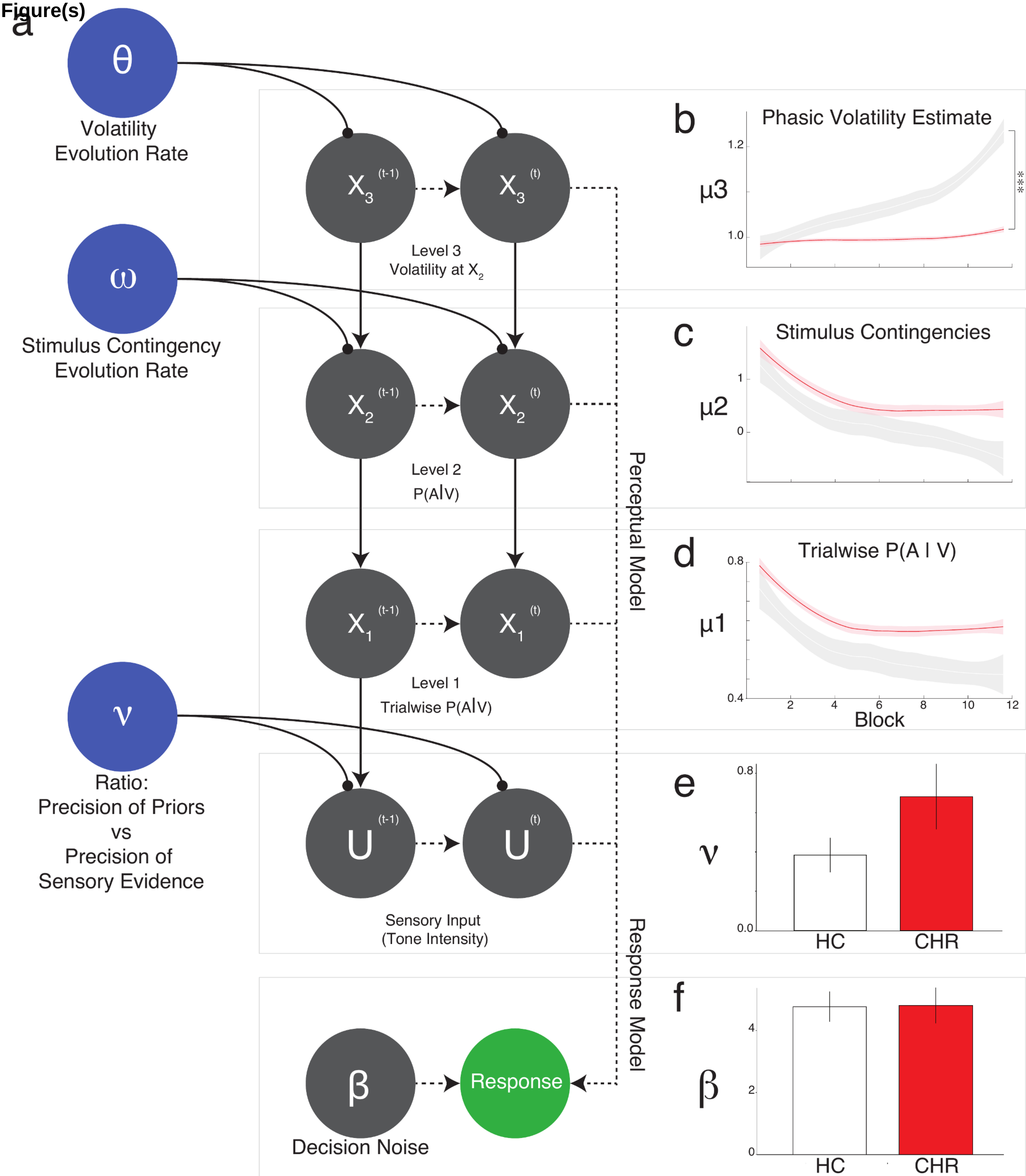


Conditioned Hallucinations (CH) Task
Sine-Vocoded Speech (SVS) Task
a
Training
Test
V
A
1s
b
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Log Intensity (dB)
30
20
10
0
2
4
6
8
10
12
Block Number
c
Original speech
The car engine's running
The old gloves are dirty
She cut with her knife
The kitchen clock was wrong
16 Channel sine-vocoding
Intelligible
Original frequencies
Unintelligible
Flipped frequencies
Unintelligible
Flipped frequencies
Unintelligible
Flipped frequencies
+6dB
Int SVS
+6dB
Unint SVS
d
Speech? Yes/No
Int SVS
Unint SVS
Int SVS
Pre-training run
90 trials
Random order
Exposure to original sentences
Unint SVS
Int SVS
Int SVS
Post-training run
Discrimination (d') & bias (β) scored

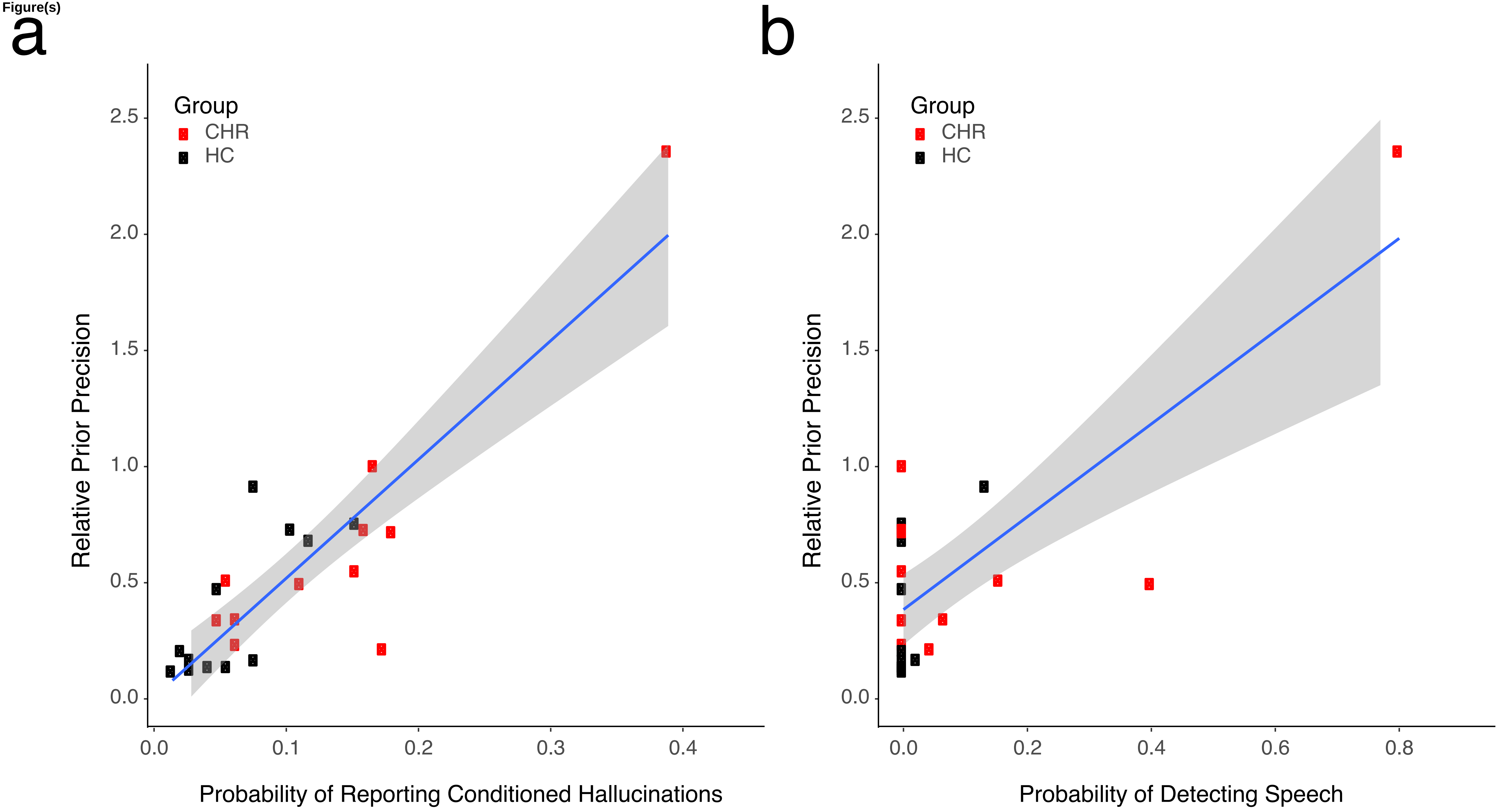
Figure(s)


a
Conditioned Hallucinations Task
*
Probability of Answering “Yes” During No−Tone Trials
0.00
0.05
0.10
0.15
HC
CHR
b
Sine-Vocoded Speech Task
*
Probability of Detecting Speech
0.00
0.05
0.10
0.15
0.20
0.25
HC
CHR
c
Group
CHR
HC
Probability of Detecting Speech
0.0
0.2
0.4
0.6
0.8
0.0
0.1
0.2
0.3
0.4
Probability of Reporting Conditioned Hallucinations

Figure(s)


a
θ
Volatility Evolution Rate
ω
Stimulus Contingency Evolution Rate
ν
Ratio: Precision of Priors vs Precision of Sensory Evidence
X3 (t-1)
X3 (t)
Level 3
Volatility at X2
X2 (t-1)
X2 (t)
Level 2
P(A|V)
X1 (t-1)
X1 (t)
Level 1
Trialwise P(A|V)
U (t-1)
U (t)
Sensory Input
(Tone Intensity)
β
Decision Noise
Response
Perceptual Model
Response Model
b
Phasic Volatility Estimate
μ3
1.2
1.0
***
c
Stimulus Contingencies
μ2
1
0
d
Trialwise P(A | V)
μ1
0.8
0.4
2
4
6
8
10
12
Block
e
ν
0.8
0.0
HC
CHR
f
β
4
2
0
HC
CHR

Figure(s)


a
b
Group
CHR
HC
Relative Prior Precision
Probability of Reporting Conditioned Hallucinations
Probability of Detecting Speech
0.0
0.5
1.0
1.5
2.0
2.5
0.1
0.2
0.3
0.4
0.6
0.8

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Contributors

Tasks set up by ARP, PRC, BAD, SE, and SB. Data were collected by team of VAM, GPS, HCC. Significant intellectual contributions from LME, JMG, SMS, EFW, SWW, PRC. Data analyzed, figures created, and manuscript written and edited by EK and ARP. Further edits from PRC, VAM, GPS, LME, JMG, AD, SE, and SMS.

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Conflicts of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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