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Conditioned hallucinations and prior over-weighting are state-sensitive markers of hallucination susceptibility

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Abstract

Recent advances in computational psychiatry have identified latent cognitive and perceptual states that predispose to psychotic symptoms. Behavioral data fit to Bayesian models have demonstrated an over-reliance on priors (i.e., prior over-weighting) during perception in select samples of individuals with hallucinations. However, the clinical utility of this observation depends on the extent to which it reflects static symptom risk or current symptom state. To determine whether task performance and estimated prior weighting related to specific elements of symptom expression, a large, heterogeneous, and deeply-phenotyped sample of hallucinators (N = 249) and non-hallucinators (N=209) performed the Conditioned Hallucination (CH) task. We found that CH rates could predict stable measures of hallucination status. However, CH rates were more sensitive to hallucination state, significantly correlating with hallucination severity measures over the two days leading up to task completion and driven by heightened reliance on past experiences (priors). To further test the sensitivity of CH rate and priors to symptom severity, a subset of participants with hallucinations (AH+; N = 40) performed a repeated-measures version of the CH task. Changes in both CH frequency and relative prior weighting varied with changes in AH

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frequency on follow-up. These results support the use of CH rate and prior over-weighting as state markers of hallucination status, potentially useful in tracking disease development and treatment response.

Keywords

computational psychiatry; hallucinations; perception; psychosis; nosology

Introduction

Progress in medicine requires an understanding of how abnormalities in underlying mechanisms of diseases lead to observable signs and symptoms. If these causes are identified, strategies for prevention and treatment can be designed specifically to arrest the processes leading to disease[1]. For instance, identifying the biochemical pathways that cause unchecked cellular proliferation in chronic myelogenous leukemia (CML) led to specific interventions arresting these pathways. Since the advent of these interventions, CML has gone from an illness with a survival of 3–5 years after diagnosis to fewer than 1% of patients dying from the disease[2].

Understanding underlying disease processes can lead to the identification of biomarkers proximal to symptom expression. These markers may then serve as useful ways of tracking disease trajectory in individuals at elevated risk and those undergoing treatment. For example, in endocrinology, risk for hypothyroidism as well as treatment response may be tracked by thyroid stimulating hormone (TSH). Elevated TSH reflects an under-performing thyroid, and likelihood of symptom expression related to that hypofunction is directly associated with serum TSH levels[3]. Thus, while TSH is not a directly observable sign or symptom, tracking this biomarker is essential to monitoring a patient's disease state.

As with CML and hypothyroidism, identifying underlying pathways and monitoring markers of disease states is important for psychiatric disorders. In psychiatry, disease states are thought to arise because of abnormalities in information processing. Like serum TSH levels, these abnormalities may not be directly observed but may be causally related to symptom expression. One promising route toward identifying biomarkers of information processing abnormalities driving psychiatric symptom expression comes from computational psychiatry[4–6]. Computational psychiatry provides mathematical frameworks for understanding the typical functioning of perceptual and cognitive systems, and how specific disturbances may lead to specific psychiatric symptoms[5,6]. One such computational framework, predictive processing theory (PPT), has proven useful in proposing mechanisms by which psychotic symptoms and brain states might arise from aberrations in learning and inference[7–9]. This approach has demonstrated promise as a tool for understanding hallucinations. Within PPT, perception is formally described as the process of inferring one's surroundings by combining their internal model of (or expectations about) those surroundings (priors) with the available sensory evidence, weighted by the reliability of their priors and sensory evidence[10–12]. Given this formulation of perception, hallucinations--

percepts in the absence of a corresponding stimulus--may arise due to over-weighted priors relative to the weight exerted by incoming sensory evidence[9,13].

Empirical support for this idea has mounted over recent years[14]. Several behavioral tasks sensitive to relative prior-weighting[15–18] have demonstrated a relationship to hallucination propensity across clinical and non-clinical populations[16,19] as well as neurological and psychiatric disorders[17]. Critically, an over-weighting of perceptual priors does not appear to be present in individuals with psychosis-spectrum disorders without hallucinations[19], suggesting specificity of this abnormality to hallucinations and not psychotic illness writ large.

Though this combination of evidence supports the idea that over-weighing perceptual priors is linked to a susceptibility toward hallucinations, no data currently exist to discern exactly what the relationship between prior over-weighting and hallucination susceptibility might be. For example, does a tendency to over-weight priors represent a static risk factor that is stable over time? Or does this tendency reflect changes in hallucination intensity that vary with current clinical state and treatments? These distinctions could reveal crucial information about the pathophysiological pathways leading directly to symptom expression and whether biomarkers based on this observation could be useful to track susceptibility toward hallucinations or response to treatment.

Here we present data from a large, heterogeneous, extensively phenotypically characterized group of individuals with unusual perceptual experiences, including those with (AH+; N=249) and without (AH-; N=209) auditory hallucinations. Participants completed the Conditioned Hallucinations (CH) task, which has previously been shown to be sensitive to prior over-weighting and propensity toward auditory hallucinations[19,20]. We replicate the findings that the CH task and estimated relative prior weighting are sensitive to hallucination propensity. We then extend these findings to demonstrate a strong relationship between prior weighting and severity of hallucinatory experiences. Lastly, we show that changes in prior weighting are in fact sensitive to changes in recent hallucination frequency, as demonstrated in a subset of individuals who performed repeat assessment.

Methods and Materials

Participants and Data Collection

Participants aged 18–65 completed a battery of demographic measures, clinical scales, and behavioral tasks as part of the Yale Control Over Perceptual Experiences (COPE) Project (https://www.spirit.research.yale.edu/). The study was coordinated through Yale's instantiation of Research Electronic Data Capture (REDCap@Yale). REDCap is a HIPAA-secure web-based software platform designed for data capture in research studies[21,22].

Recruitment was accomplished via advertising through specific partners (https://www.spirit.research.yale.edu/partners) who work with individuals with unusual perceptual experiences and unusual beliefs, both with and without a need for care, as well as broader posting via Amazon Mechanical Turk and social media platforms. All procedures were approved by the Yale University Institutional Review Board / Human Interest Committee.

Participants provided informed consent and received monetary compensation for their participation, contingent on adequate completion of all study procedures. A screening survey excluded those who reported cognitive, neurological, or seizure disorders or endorsed being under the influence of recreational drugs or alcohol at participation.

Phenomenological and Clinical Battery

Participants were screened for the presence of auditory hallucinations (AH) via administration of the screening portion of the Chicago Hallucination Assessment Tool (CHAT) by online self-report[23]. This tool also provided an estimate of the frequency and recency of hallucinations across modalities. AH+ participants also completed the Computerized Binary Scale for Auditory Speech Hallucinations (cbSASH)[24], the Beliefs About Voices Questionnaire-Revised (BAVQ-R)[25], the Launay-Slade Hallucination Scale-Revised (LSHS-R)[26,27], and the Yale Control Over Perceptual Experiences Scale[28]. All participants also provided past psychiatric history (including medications) and completed the Peters et al Delusion Inventory (PDI)[29], the 9-item version of Raven's Progressive Matrices[30], and the Miller-Forensic Assessment of Symptoms Test (M-FAST)[31].

Auditory Conditioned Hallucinations (CH) Task

The CH task is a sensory-detection task using principles of psychometric thresholding and Pavlovian associative learning[19,20,32–35] to induce auditory hallucinations[19,20]. Participants press buttons to indicate their detection of a target stimulus, a 1-kHz pure tone embedded in 70-dB SPL white noise and presented concurrently with a flashed white checkerboard on a black background (Fig. 1a).

The online CH task was implemented via React (https://reactjs.org/), using the same structure as previous versions. Participants used the *q* and *e* keys to indicate 'yes' or 'no' for detection of the tone, and held these keys down to indicate confidence in their responses using a color visual analog scale from "Unsure" (1) to "Certain" (5). Participant non-response triggered a trial repeat. 80% accuracy on two short practice sessions was required before task initiation. Thresholding was accomplished via two 40-trial interleaved staircases with step sizes computed by QUEST, a maximum-likelihood based procedure adapted to JavaScript from Psychtoolbox 3.0[19,36]. QUEST determined the volume at which participants would detect the tone 75% of the time. A psychometric function was fitted to ascertain based on the 75%-values and used to determine the 25% and 50% thresholds[37] (Fig. 1b, left). Over 12 blocks of 30 pseudorandomized trials, the likelihood of tone presentation at previously-computed intensities decreased non-linearly, while the likelihood of sub-threshold target presentation and no-tone trials increased (Fig 1c, right). We calculated detection probability for each trial type as the proportion of all trials for which participants indicated 'Yes' for target stimulus detection at that stimulus intensity. Trials in which participants signaled detection despite absence of the target stimulus were reported as conditioned hallucination trials.

Sample Selection

A sample of 458 participants from the Yale COPE Project were selected after quality control procedures and demographic matching (see Supplemental Methods for details).

Participants with AH (AH+) and without AH (AH-) were identified by CHAT-AH score. Any endorsement of CHAT-AH items 4 through 8 was considered as AH+ (Table S1)[38], as items 1–3 ("Have you ever thought you heard someone call your name, but then realized you must have been mistaken?"; "Have you ever heard your phone ringing, but then realized the phone hadn't actually rung?"; and "Do you ever hear strange noises when you are falling asleep or waking up in the morning?") are very commonly endorsed in the general population[39–41]. A random sample, balanced in age, sex, and total score on the Raven's progressive matrices between the AH+ and AH− groups, was selected for between-group analyses. The AH+ group was further divided based on the frequency of the hallucinations reported (Daily, Weekly, Monthly or Less), based on the highest frequency endorsed for any CHAT-AH items 4 through 7.

Hierarchical Gaussian Filter (HGF) Analysis

To identify the latent states driving behavior on the CH Task, we fitted parameters of a three-tiered Hierarchical Gaussian Filter (HGF) using trial-wise data on stimulus intensity and responses[42,43]. Given the heterogeneity of hardware systems utilized in this online sample, empirically-derived grand mean detection rates at each condition were used as stimulus intensity inputs. The HGF is a computational Bayesian hierarchical model of learning and inference in a changing environment[44]. This model has been adapted for CH data[19,20] (Fig. 3a). For this task, inference on the first level (X_1) represents trial-wise participant belief in the presence of the target given the visual stimulus, inference on the second level (X_2) models the belief that the visual stimulus predicts the target auditory stimulus, and inference on the third level (X_3) is the participant's estimated volatility of the contingency between the visual and target stimuli (i.e., volatility of X_2). μ refers to the means of inferred beliefs about X_1-X_3, v to individual subjects' relative weighting of priors and sensory input, and ω_2 and ω_3 to belief evolution rates on levels 2 and 3. Beliefs about the presence of the target on any given trial (mu1) are combined with tone intensity and weighted according to the parameter v to produce posterior beliefs about the presence of the tone on any given trial. Higher v values correspond to a higher weighting of perceptual beliefs relative to sensory evidence. Posterior perceptual beliefs about the presence of the target stimulus given available sensory evidence are fed into a response model, which estimates the likelihood of a response taking into account decision noise (β^{-1}). Additional details of HGF implementation using CH task data, including comparison of multiple models, are included in the Supplement and have been published elsewhere[19,20]. Relevant model code has been made freely available as part of the TAPAS computational toolbox (github.com/translationalneuromodeling/tapas). As was done in prior work, different HGF models were tested to ensure suitability of the model employed (Fig. S1).

Re-test sample and procedures

In order to assess for changes in task performance that may relate to changes in clinical status, all COPE participants who completed initial assessments were invited to complete an additional follow-up assessment. Final re-test sample characteristics are outlined in Table S2. Participants repeated CHAT screening questions to assess for changes in hallucination state, in addition to the COPE scale, BAVQ-R, LSHS-R, and the CH task. To minimize transfer of prior learning, follow-up versions of the CH task used novel stimulus pairs, as

cross-modal perceptual learning tends not to transfer across stimulus sets[45–47]. To allow for re-test at multiple time points per participant, stimulus pairs depended on time elapsed since initial assessment, although only one follow-up point was used for analysis: red horizontal stripes were used for individuals at first follow-up (<8 months after initial assessment); 45° blue stripes were used at second follow-up (>8 months after first assessment). Stripes were matched for luminance, complexity, and contrasts compared to the original stimulus set. Similarly, auditory stimuli used tones of 1250 Hz (first follow-up) and 1500 Hz (second follow-up). Otherwise, the structure and procedure of the task was as outlined above in the original task. For purposes of quantifying changes in hallucination frequency on follow-up assessment, hallucination frequency categories (e.g., "Once per week") were converted to minimum occurrence rates over days (e.g., 1/7). To avoid divide-by-zero errors, relative changes were calculated as log ratios of final rates over initial rates.

Statistical Analysis

Differences between AH- and AH+ groups were computed using two-sample t-tests and Wilcoxon tests as appropriate. For comparisons of means across frequency groups, one-way ANOVA was used. Correlations were computed using Pearson correlations. All statistical analyses were completed using the R packages *tableone, plotrix, car, nlme* and *afex* performed with RStudio version 1.4.1717 (http://www.rstudio.com/).

Results

Sample Characteristics

Table 1 reports the summary of the demographic and clinical features of our final balanced sample. The AH+ group (N=249) obtained significantly higher scores in propensity for hallucinations (LSHS) (T_{135}=10.0, p<0.001) and delusions (PDI) (T_{426}=14.5, $p<2.2\times10^{-16}$) than the AH− group (N=209). AH+ also reported a higher frequency of psychosis-spectrum illness (χ_1^2=20.4, p<0.001), mental illness in general (χ_1^2=35.1, p<0.001), and used more psychiatric medication (χ_1^2=29.3, p<0.001) than AH-. The groups did not differ significantly on age, sex, or reported race.

Conditioned hallucination rates and confidence are higher in AH+

AH+ and AH− groups did not differ on the QUEST-derived threshold (Fig. 2a), but AH+ participants were more likely to report CH (T_{450}=2.71, $p=6.9\times10^{-3}$; Fig. 2b). This difference survived after controlling for the presence of self-reported psychotic-spectrum illness (by ANCOVA; $F_{1,455}$=1, $p=6.2\times10^{-3}$) and limiting responses to only those with high confidence (T_{446} = 2.50, p = 0.013). Similarly, effects survived when the AH+ group was extended to include those who indicated yes on any item 1–8 in the CHAT-AH (N = 360) and those who reported no on all items (N = 98; T_{161} = 2.549, p = 0.012). Significant differences between AH+ and AH− groups emerged early during the fourth block of the experiment, at the twenty-sixth presentation of a no-tone trial (Fig. 2d). Maximal statistical difference was noted at trial 62 ($T_{455=}$3.27, $p=1.2\times10^{-3}$). Performance did not differ significantly on any other conditions (Fig. S2).

Pertaining to confidence ratings, there was a significant interaction between the answer choice and condition ($F_{6,4966}$=529, p=2×10^{-16}): participants were more confident reporting detection and less confident reporting non-detection with increasing target loudness. There was a significant interaction between hallucination status and condition ($F_{3,4966}$=2.7, p=0.045). Participants with hallucinations had higher confidence in reporting conditioned hallucinations (T_{427}=2.23, p=0.026).

Conditioned hallucination rates and confidence ratings scale with severity of auditory hallucinations

Probability of reporting CH varied significantly according to the frequency of reported hallucinations (Fig. 2f; $F_{3,445=}$7.68, p=5.0×10^{-3}; r_{445}=0.13, p=6.0×10^{-3}). Significant differences emerged early (no-tone trial 28) and hit their maximum again at no-tone trial 62 ($F_{3,445}$ =12.1; p=5.9×10^{-3}; Fig. 2h). Post-hoc differences were evident between Daily and AH− (T_{62}=2.14, p=0.036) as well as Monthly and AH− (T_{304}=2.15, p=0.032) groups. Participants also completed the Peters Delusion Inventory to assess delusional ideation. Individuals with higher CH rates reported higher delusional ideation (r_{456} = 0.004, p = 0.0215). However, this relationship did not persist after accounting for current frequency of hallucinations ($F_{1,448}$ = 2.599, p = 0.108). Similarly, within the AH+ group who completed the Launay-Slade Hallucination Scale, PDI was no longer a statistically significant predictor of CH rate ($F_{1,210}$ = 1.492, p = 0.223) after accounting for LSHS total scores (R_{211} = 0.149, $F_{1,210}$ = 4.824, p = 0.0292)

We further investigated if the relationship between CH rate and hallucination status reflected current or overall susceptibility to hallucinations within participants who reported having hallucinations and completed detailed phenomenological surveys about their hallucinations (n=220). CH rates significantly correlated with hallucination frequency within the last two days (r_{218}=0.13, p=0.042), and not with the frequency of hallucinations at the ‘worst time’ in their history (r_{218}= 0.12, p=0.12).

Confidence ratings in reporting CH were significantly different between frequency groups ($F_{3,435}$=4.98, p=0.026). Post-hoc analyses showed that the difference between Daily and AH− was significant (T_{70}=4.98, p=0.021).

Relative prior weighting is higher in those who hallucinate and is associated with frequency of auditory hallucinations

To evaluate latent factors driving performance on the CH task, we fit participants’ behavioral data to a three-tiered model of perception, the Hierarchical Gaussian Filter (HGF)[42,43], which we have done in past work[19,20] (Fig. 3a). The HGF is particularly useful in its ability to directly model the degree to which participants rely on their priors when making perceptual judgments (relative prior weighting, ν). The AH+ group exhibited higher prior weighting (T_{451}=2.3, p=0.021) (Fig. 3c) but not belief trajectories (X_1-X_3) (Fig. 3b) or decision noise (β^{-1}) (Fig. 3c).

The relative prior weighting parameter (ν) was found to vary according to frequency of auditory hallucinations ($F_{1,445}$=7.42, p=6.6×10^{-3}; R_{445}=0.13, p =7.0×10^{-3}). Conversely, there was no difference in decision noise (β^{-1}) between frequency groups.

The HGF also models the rate at which participants learn to associate the auditory stimulus with the stripes (ω2). This rate of association-building was found to decrease with increases in cognitive functioning, based on Raven's Progressive Matrices score ($R_{456} = -0.15$, $p = 1.16 \times 10^{-3}$).

Changes in conditioned hallucinations and prior weighting vary with changes in auditory hallucination frequency.

A subset of participants (N = 40; see Table 1 for sample characteristics) completed a repeated-measures version of the CH task several months (mean±SD = 375.54 ± 113.99 days) after initial performance. Those who did not report auditory hallucinations at baseline or during follow-up assessments(N = 6) were excluded from final analyses. As shown in Figure 4a, those who reported an increase in hallucination frequency during follow-up sessions showed higher rates of conditioned hallucinations relative to their initial CH rate than those with decreased hallucination frequency ($p = 0.026$, $r = 0.377$, power = 0.808), while those with no change in frequency exhibited no change in conditioned hallucination rate. Correlation analysis corroborated this relationship: changes in AH frequency were associated with both changes in conditioned hallucination rate (Fig. 4b; $r_{28} = 0.40$, $p= 0.028$,) and changes in relative prior weighting (Fig. 4c; $r_{28} = 0.378$, $p = 0.039$), adjusted for baseline rates. Consistent with Figure 3, changes in conditioned hallucination rate correlated with changes in relative prior weighting (Fig. 4d; $r_{33} = 0.594$, $p = 1.7 \times 10^{-4}$).

Discussion

In a large, heterogeneous sample of individuals with hallucinations, we have provided evidence for a link between conditioned hallucinations, relative prior weighting in perception, and recent hallucination frequency. Previous work highlights the relationship between relative prior weighting and auditory hallucinations in small sub-groups of people who frequently heard voices with distinctly clear acoustic qualities[16,19]. In the data we present here, inclusion of individuals with a broad range of phenomenological characteristics, daily functioning, and clinical needs allowed us to examine the performance data and model parameter estimates for relationships to each of these quantities. As we have done in prior work[19], we relate auditory conditioned hallucination rates to a propensity toward hallucinations in our diverse sample, both categorically and dimensionally, as measured by LSHS-R score. Rates of CH were lower in this diverse AH+ sample compared to previous highly-selected samples; however, examining CH rates and estimated relative prior weighting in sub-groups of individuals with daily hallucinations (Figs. 2, 3) yields estimates that closely approximate previously-reported rates[19] despite wide variance in software and hardware implementation as well as stimulus set (see Figs. S3–S5).

Relationships between prior weighting, conditioned hallucinations, and frequency of hallucinations are evident throughout the data set. Conditioned hallucination rates and prior weighting are higher in high-frequency hallucinating groups on cross-sectional analysis (Figs. 2 and 3) and track with changes in frequency of hallucinations during follow-up sessions even after adjustment for baseline frequency (Fig. 4). Our findings that the relative weighting of priors is both higher in individuals who hallucinate and sensitive to

changes in symptom severity suggests that relative prior weighting captures both static and dynamic elements of hallucinations. If increased prior weighting increases the likelihood of experiencing hallucinatory events, it may represent a latent brain state or mode of functioning that leads proximately to those events. This may be contrasted against other elements that, although increasing lifetime risk of having hallucinations (e.g., a history of trauma), do not translate to symptom severity on a more granular scale. While it is conceivable that these measures could lead directly to clinically useful tests in their current form, they are likely more useful as a means of identifying individuals exhibiting specific vulnerabilities toward hallucinations that may be intervened upon specifically to decrease hallucination severity. However, future interventional studies are required to understand the exact temporal relationships between prior weighting and hallucination expression before hard conclusions can be drawn.

Our results contribute to the growing literature exploring computationally-derived biomarkers in psychiatry[6,49,50]. Biomarkers with some sensitivity to current symptom severity are able to track dynamic changes in symptomatology, capturing clinical worsening or improvement in response to treatment[50,51]. Returning to the example provided in the Introduction, psychosis, like hypothyroidism, has been conceptualized as a disease state[52] that may be tracked by state-sensitive measure–like TSH–to detect progression toward development of psychotic symptoms like hallucinations as well as response to treatment. We have recently demonstrated that individuals at clinical high risk for psychosis (CHR-P) tend to rely on their priors[20,53], which supports the usefulness of this measure in tracking risk for clinical worsening before the onset of frank psychosis. Further work is required to demonstrate an extension of this vulnerability even earlier in the trajectory of psychotic illness, but it opens up the intriguing possibility of using our measures to track symptom susceptibility before the onset of any symptoms whatsoever among those who already exhibit a static risk for disease development[54]. This latter approach would allow for a more nuanced understanding of pathophysiology, where the interplay between static risk factors (such as gene expression) lead to a worsening of dynamic, state-sensitive markers of symptom susceptibility.

From the perspective of computational neuroscience, the fact that relative prior over-weighting can vary significantly over time yields important clues as to its neural instantiations. Although aberrations in synaptic density[55], cortical morphology[56–58], and white matter integrity[59] increase psychosis risk, it is unlikely that these processes directly drive prior weighting. Rather, these factors may predispose to the development of neural states in which prior weighting is dynamically heightened, either absolutely or relative to degraded and unreliable sensory evidence. Due to the short timescales over which changes in Bayesian inference have been observed, any neural mechanisms underlying these changes (e.g., phasic neuromodulator release) must also be dynamic.[7,9,60]. This is largely consistent with recent findings that prior weighting is related to dopamine synthesis capacity[18], and that cholinergic modulation affects reliance on the weighting afforded to sensory evidence[61]. Further research is needed to assess the relationship between these processes and other known dynamic factors at play in psychosis, such as glutamatergic neurotransmission and excitation / inhibition balance[62]. Recent evidence explicitly links disinhibition of pyramidal cells in auditory cortex to perceptual abnormalities in early psychosis[63], and there may

plausibly be a role for several neuromodulatory systems in the perceptual processes we describe here.

The identification of a computationally-driven method of identifying risk factors in individuals with hallucinations is the first step toward individualized risk and treatment prediction based on distinct etiologies[64]. The current work extends these efforts by identifying parameters within a specific, formalized model of perception that may lead to hallucination expression. We anticipate that subgroup identification based upon such a formal system may take advantage of emerging knowledge of the neural[18,19] and biochemical[61] underpinnings of prior weighting to identify biologically-based interventions most likely to alter the pathophysiological processes leading to initial symptom expression.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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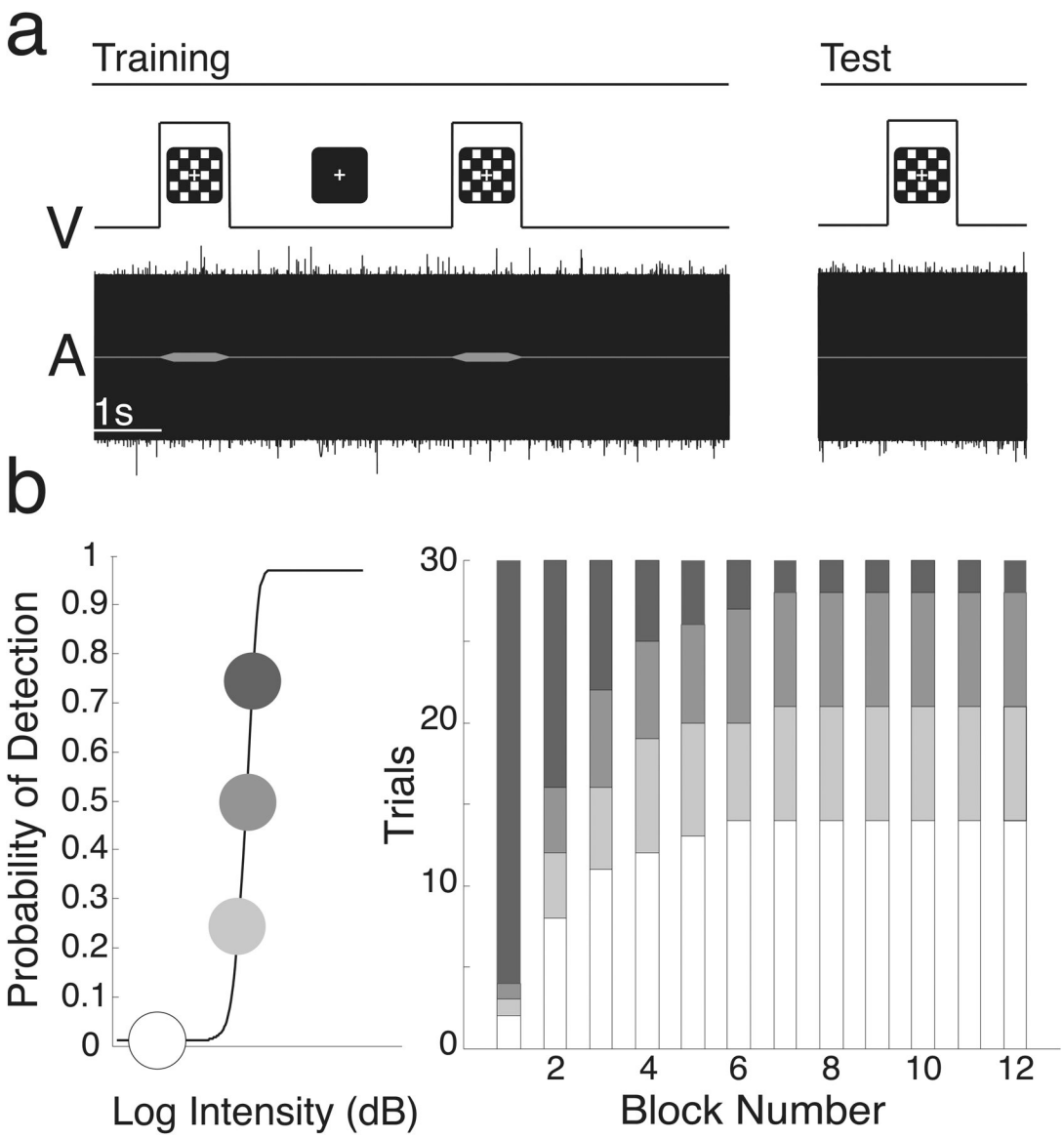

Figure 1. Auditory Conditioned Hallucinations (CH) Task Structure.

a. Visual and auditory stimuli and task structure. Trials consisted of simultaneous presentation of a 1000-Hz tone embedded in white noise and a visual checkerboard. **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 absent tones were more likely later (right).

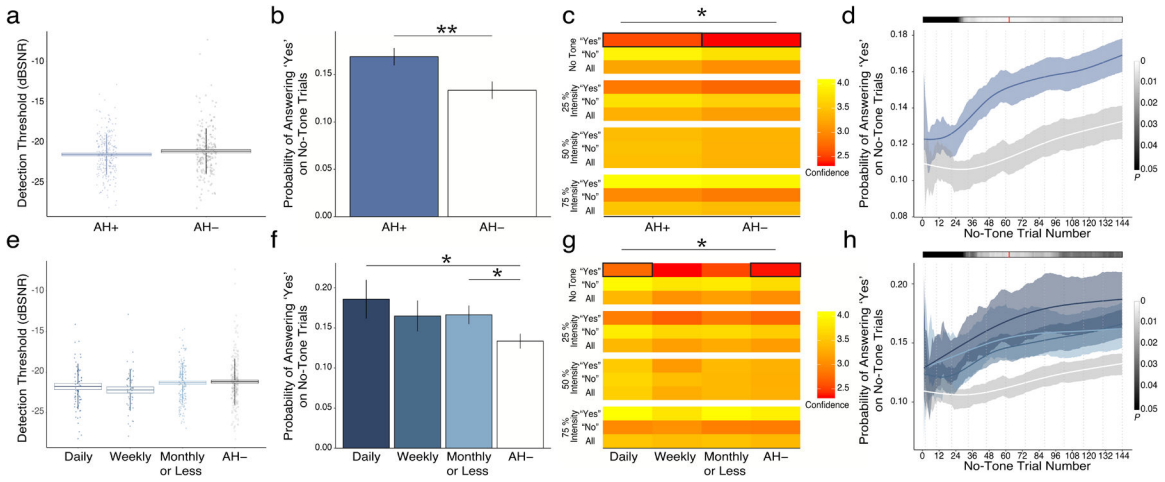

Figure 2. Behavioral Results.

a. Calculated thresholds for tone detection were similar to those previously reported[19,20] and did not differ between hallucinating (AH+) and non-hallucinating (AH-) groups. **b.** Probability of reporting CH was significantly higher in AH+ than in AH− groups. **c.** Confidence in reporting CH was also higher in AH+ than in AH− groups. **d.** Trial-wise analysis of the emergence of behavioral effects demonstrated early differences in means that became significant in experimental block 4 and reached their maximum in early block 7 of 12. AH+ was divided into three groups based on reported hallucination frequency: Daily (N=49), Weekly (N=43), and Monthly or Less (N=146). Results parsed by frequency of clinical hallucinations demonstrated similar lack of differences in threshold (**e**), but showed that probability of (**f**) and confidence in (**g**) reporting CH differed significantly by frequency of voice-hearing. **h.** Emergence of behavioral effects showed a similar profile to group-wise effects in panel **d** and means effects in panel **f**.

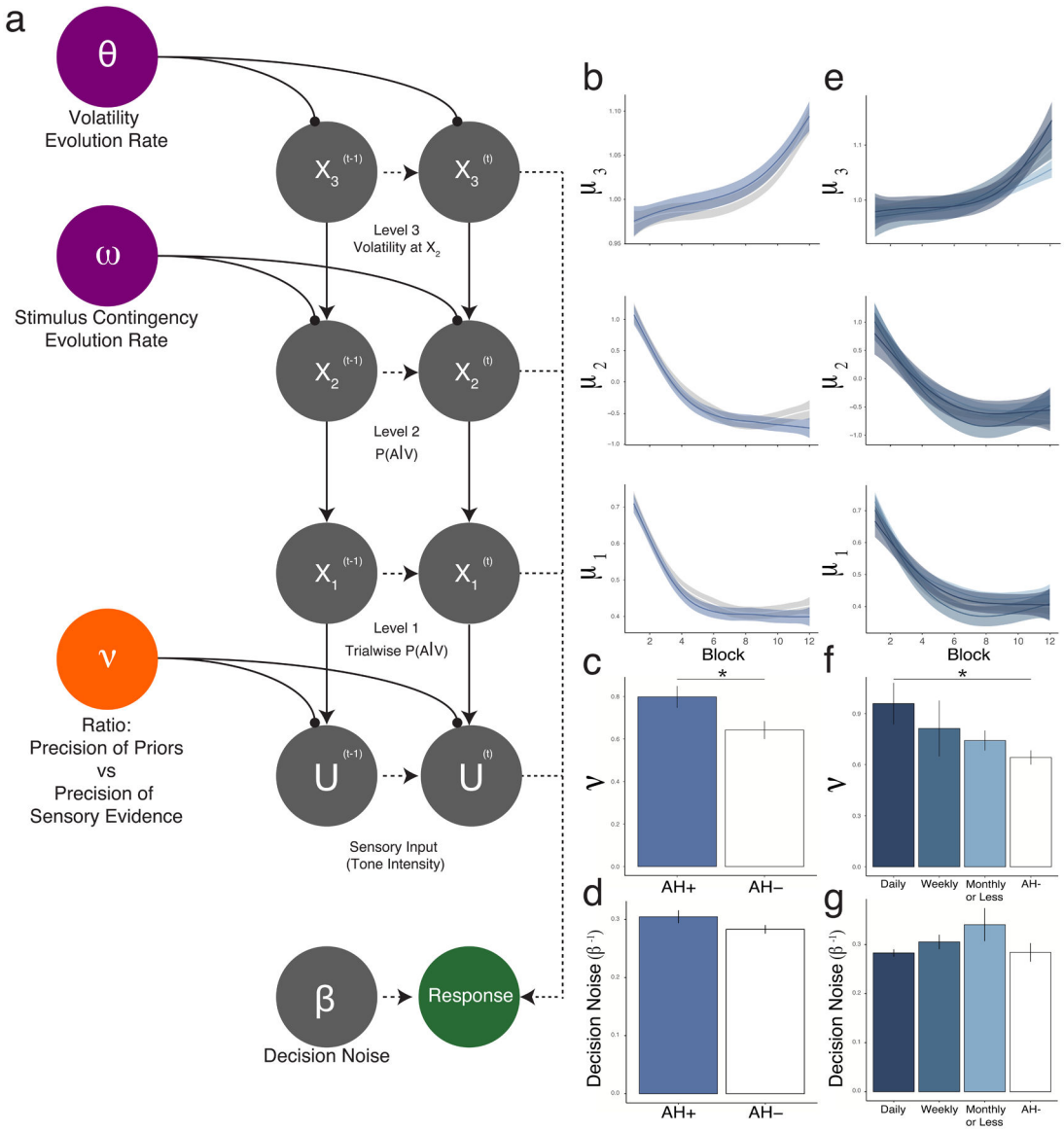

Figure 3. Hierarchical Gaussian Filter (HGF) Analysis.

a. HGF model, mapping the combination of latent states (e.g., trajectories X_1-X_3, relative prior weighting v, inverse decision temperature / decision noise β^{-1}, evolution rates ω and θ) to recorded responses, taking into account trial-wise stimulus strength (U). The first level (X_1) represents the target tone's presence on trial t. The second level (X_2) represents the contingency between the visual and auditory stimuli. The third level (X_3) represents the volatility of the relationship between the visual and auditory stimuli over the course of the experiment. Critically, responses are modelled allowing for individual variation in weighting between sensory evidence and perceptual beliefs (parameter ν). **b-g.** Belief trajectories do not differ between AH+ and AH− groups at any level (**b**), nor did decision noise (**d**), whereas prior weighting was greater in AH+ than in AH− (**c**). A similar pattern of results was seen when participants were divided into frequency groups, which did not differ in

belief trajectories (**e**) or decision noise (**g**). By contrast, relative prior weighting (**f**) scaled with hallucination frequency.

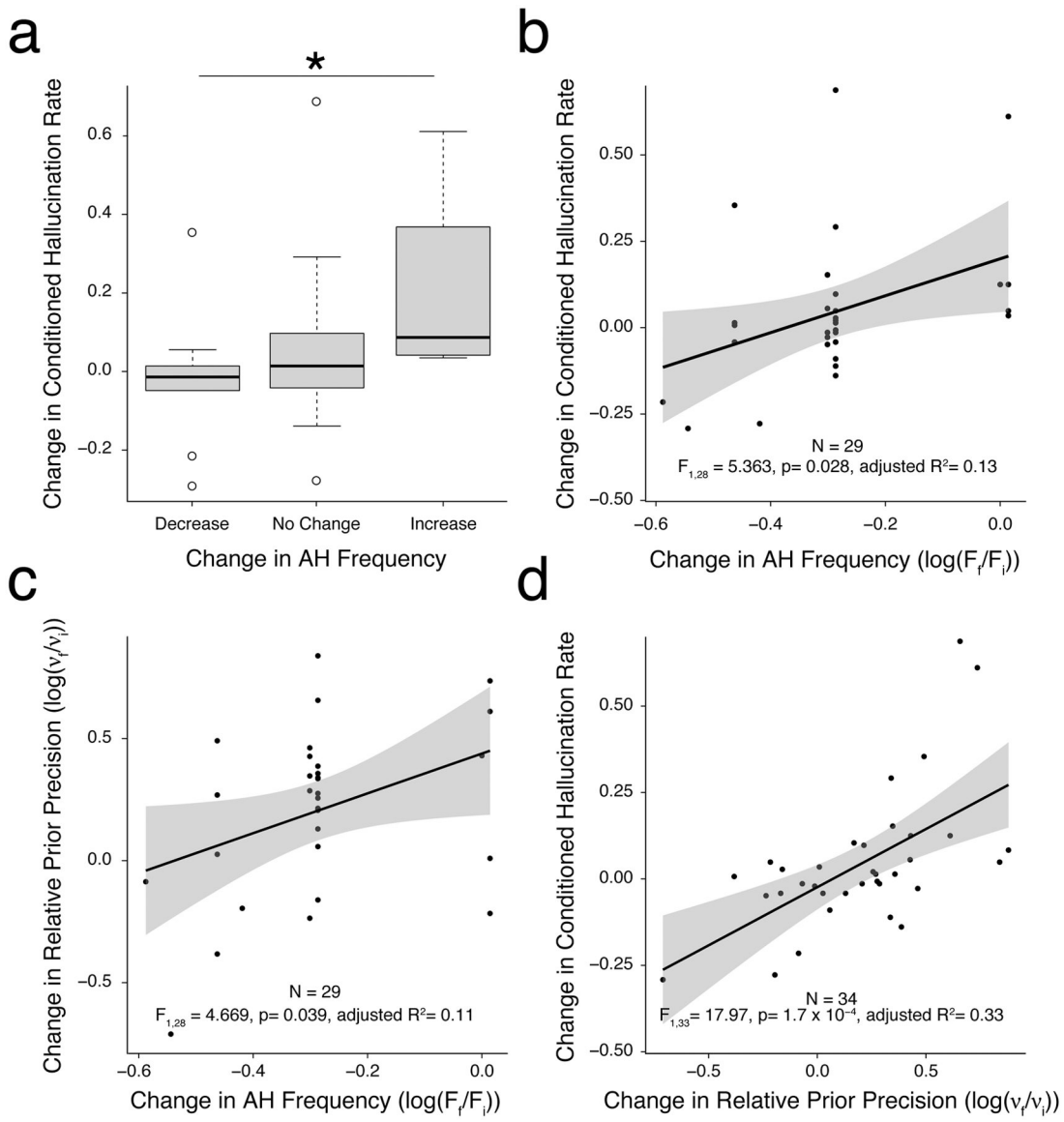

Figure 4. Changes in conditioned hallucinations and prior weighting vary with changes in auditory hallucination frequency.

a. In a sub-sample of AH+ participants who performed a repeated-measures version of the CH task again after several months, those with an increase in hallucination frequency showed a higher rate of conditioned hallucinations than those with a decrease, while those without a change in frequency demonstrated no change in conditioned hallucination rate. **b-d.** Correlations demonstrating both conditioned hallucinations rate (**b**) and relative prior weighting (**c**) track with changes in AH frequency on follow-up, and that changes conditioned hallucinations rate are attributable to changes in prior weighting (**d**). *, $p < 0.05$.

Table 1.

Sample demographic and clinical characteristics of original and follow-up samples.

	AH−	AH+	P	Follow-up
n	**209**	**249**		**40**
Age (mean (SD))	37.78 (10.95)	38.17 (13.75)	0.741	39.5 (15.81)
Total LSHS Score(mean (SD))	5.91 (6.12)	16.28 (9.38)	**<0.001**	11.18 (11.07)
Total PDI Score(mean (SD))	1.96 (2.65)	6.63 (4.17)	**<0.001**	6.18 (4.67)
Self Report, Mental Illness n(%)	18 (10.2)	88 (36.1)	**<0.001**	15 (37.5)
Race n(%)			0.384	
American Indian/Alaskan Native	5 (2.4)	2 (0.8)		0 (0.0)
Asian	19 (9.1)	28 (11.2)		7 (17.5)
Native Hawaiian or Other Pacific Islander	1 (0.5)	2 (0.8)		0 (0.0)
Black or African American	6 (2.9)	8 (3.2)		0 (0.0)
White	164 (78.5)	185 (74.3)		30 (0.75)
More than one race	7 (3.3)	18 (7.2)		3 (7.5)
Unknown/Prefer not to say	7 (3.3)	6 (2.4)		0 (0.0)
Sex F n(%)	121 (57.9)	166 (66.7)	0.066	28 (70.0)
Current Medication Use n(%)	10 (4.8)	58 (23.3)	**<0.001**	9 (22.5)
Self Report, Psychosis Spectrum Illness n(%)	1 (0.5)	28 (11.2)	**<0.001**	3 (7.50)
Total Raven Score (out of 9) (mean (SD))	6.36 (1.69)	6.07 (1.83)	0.079	5.00 (0.41)