Cross-modality evidence for reduced choice history biases in psychosis prone individuals

Authors:

Anna-Lena Eckert[1,2,3], Yael Gounitski[3], Matthias Guggenmos[3*], Philipp Sterzer[2,3*]

Affiliations:

[1] Charité – Universitätsmedizin Berlin, Einstein Center for Neurosciences Berlin, Charitéplatz 1, 10117 Berlin, Germany
[2] Bernstein Center for Computational Neuroscience Berlin, Unter den Linden 6, 10099 Berlin, Germany
[3] Department of Psychiatry and Neurosciences, Campus Mitte, Charité – Universitätsmedizin Berlin, Charitéplatz 1, 10117 Berlin, Germany
* equal contribution

Corresponding author:

Anna-Lena Eckert, M.sc., Department of Psychiatry and Neuroscience, Campus Mitte Charité – Universitätsmedizin Berlin, Charitéplatz 1, 10117 Berlin
e-mail: anna-lena.eckert@charite.de

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Abstract

Background. Predictive processing posits that perception emerges from inferential processes within a hierarchical cortical system. Alterations of these processes may result in psychotic experiences, such as hallucinations and delusions. Central to the predictive processing account of psychosis is the notion of aberrant weights attributed to prior information and sensory input across the cortical hierarchy. Specifically, aberrant perceptual inference in psychosis has been proposed to result from decreased reliance on priors at low hierarchical levels.

Study Design. We investigated the relationship between choice history biases in perceptual decision-making - as a proxy for low-level priors - and psychosis proneness in the general population. Choice history biases and their adaptation to experimentally induced changes in stimulus serial dependencies were investigated in decision-making tasks with auditory *(Experiment 1)* and visual *(Experiment 2)* stimuli. We further explored a potential compensatory mechanism for reduced choice history biases by higher-level priors based on predictive cross-modal cues.

Results. In line with our preregistered hypothesis, psychosis proneness was associated with decreased choice history biases in both experiments. This association generalized across conditions with and without stimulus serial dependencies. A compensatory reliance on high-level beliefs in psychosis prone individuals was observed in *Experiment 2,* but not in *Experiment 1*.

Conclusions. Our results support the notion of imprecise low-level priors in psychosis proneness, in line with predictive processing accounts of psychosis. A compensatory mechanism between low- and higher-level beliefs is not supported unequivocally by our data.

Keywords. Predictive processing - psychosis - choice history bias – perceptual decision-making – computational psychiatry

Main article

1 Introduction

Predictive processing theory conceptualizes prediction as a core strategy of the brain.[1,2] Since the brain does not have direct access to its surroundings, it is thought to entertain a hierarchical model of the world. This model is constrained by sensory information and constantly updated by mismatches between model predictions and sensory data (prediction errors).[3–5] In Bayesian terms, predictions and sensory information are modelled as prior belief (prior) and likelihood, respectively. They are represented by probability distributions and combined to compute an updated belief, the posterior. Critically, the weighting of prior and likelihood in computing the posterior is determined by their respective precisions: Low prior precision and high likelihood precision will result in large belief updates by precision-weighted prediction errors, and vice versa.[5,6]

It has been proposed that hallucinations and delusions, core features of psychosis, correspond to aberrant inference resulting from altered precision weighting.[4,6–10] Specifically, a reduced precision of priors, relative to the likelihood, may lead to increased precision-weighted prediction errors and thus enhanced weighting of sensory information relative to model predictions. The notion of imprecise priors is supported by the observation that individuals with psychosis are less susceptible to some visual illusions, which - in Bayesian terms - reflect reliance on precise perceptual priors.[11,12] Conversely, there is evidence for a higher sensitivity to sensory information in individuals with psychosis.[13] In an attempt to compensate for perceptual uncertainty resulting from reduced prior precision at low hierarchical levels, the psychosis-prone brain may form overly precise beliefs at higher levels.[7,10,14,15] Indeed, perceptual disturbances such as hallucinations[16,17] and the tenacious persistence of delusions in psychosis[4,10,18] have been related to increased prior precision.

A well-documented manifestation of low-level priors in perceptual inference is the influence of recent perceptual history. *Choice history biases* have been reported across a wide range of perceptual tasks and stimuli including visual motion,[19–21] orientation,[22–26] numerosity,[27,28] spatial location,[29] and face identity.[30–32] Previous studies suggest that the integration of recent perceptual experience with sensory information is an adaptive strategy to cope with uncertainty, where previous perception acts as a prior for processing sensory information.[23,33–35] Indeed, choice history biases scale with uncertainty[19,21,36,37] and adapt to environmental statistics.[21,38] Pascucci and colleagues suggested that the past influences current perception in two ways.[39] Short-term adaptation repels current perception away from past experience, while previous experience attracts perception towards the recent past. This attractive effect of previous on current perceptual choices can be conceptualized as reflecting an ad-hoc perceptual prior which shapes subsequent percepts. Choice history biases therefore offer an opportunity to quantify the influence of perceptual priors and to thereby investigate individual differences in perceptual inference in relation to psychosis.

Here, we investigated the relationship between psychosis proneness and the reliance on different types of prior information in perceptual inference. To test whether individual differences would generalize across sensory modalities, we performed two experiments with analogous perceptual tasks in the auditory and visual modalities. Participants had to make perceptual choices under uncertainty, but did not receive feedback on their choices. The formation of low-level priors thus had to rely on the participant's own perceptual inference as reflected by their choices. While choice history biases thus served as a proxy for low-level priors, higher-level beliefs were induced by cues that were predictive of the upcoming stimulus. To manipulate the relevance of low-level priors, we implemented block-wise statistical regularities so that stimuli were presented either in random- or auto-correlated order.

Our main hypothesis was that higher psychosis proneness would be associated with a reduced influence of low-level priors, i.e. smaller choice history biases. We further investigated the relationship between psychosis proneness and the reliance on cues, based on the notion that reduced low-level priors in psychosis proneness may be compensated by an increased reliance on higher-level priors. We further explored whether choice history biases adapt to block statistics and the modulation of this adaptation by psychosis proneness.

2 Methods

We conducted two behavioural experiments to investigate choice history biases in perceptual decision-making and its relationship to psychosis proneness in the general population (total N=154, a-priori sample size estimation for 0.8 power per Experiment). Both experiments were similar in structure, but differed in stimulus modality, apparatus and setting. For a more detailed description of experimental methods, see **Supplement (S)1**. Across experiments, participants with average performance levels of <60% and >90% were excluded. As stated in our pre-registrations, this maximizes statistical sensitivity for choice history effects. If performance is too low, participants may be guessing and there is no meaningful prior built over a previous percept. In contrast, near-ceiling performance indicates clear percepts, reducing the need for relying on priors. Both experiments were piloted.

2.1. Experiment 1

Experiment 1 was an online, gamified auditory perceptual decision-making task.[40] The experiment was pre-registered (asPredicted.org, #50562), approved by the ethics committee of Charité – Universitätsmedizin Berlin (#EA1/134/20) and in line with the Declaration of Helsinki. All participants gave informed consent and received a monetary reward of £7.30 (8.57 €) per hour. Participants were naïve to the purpose of the experiment and reported no hearing impairments. One-hundred-and-fifty participants were recruited via Prolific,[41] of which 113 were included in the final data set (24.7 years ± 7.34 standard deviation (SD), 75 male). The experiment was created using the Gorilla task builder.[42] In the task, trains of click sounds were presented to the participant's left- and right ear (Figure **S1**). Participants had to indicate the ear to which more click sounds were presented (*target ear* in the following). There were six levels of discriminability, determined by the difference in clicks between the left and right channel. To induce high-level beliefs about the auditory stimulus, a visual cue was presented, which predicted the target ear accurately in 75% of trials. The experiment consisted of 8 blocks à 48 trials, resulting in 384 trials (ca. 45 minutes). There were two types of blocks. In N-type (or neutral) blocks, the target ear was chosen randomly on each trial. In R-type (or repetitive) blocks, the target ear of trial $t - 1$ was repeated in trial t in 80% of cases, thus increasing the relevance of sensory-level prior information. Block sequences were either NRRNRNNR or RNNRNRRN, which were counterbalanced across participants. Several measures to ensure data quality were implemented, such as attention- and headphone checks.[43] Upon completing all 8 blocks, participants were informed about the true level of cue correctness, received global feedback about their performance and completed a debriefing questionnaire.

2.2. Experiment 2

Experiment 2 was a laboratory-based visual decision-making task using random dot kinematograms (RDKs, **S1**). The experiment was pre-registered (asPredicted.org, #71784) and approved by the ethics committee of Charité – Universitätsmedizin Berlin (#EA1/198/19). Experimental procedures were in line with the Declaration of Helsinki and all participants gave written informed consent. Fifty healthy participants without a history of psychiatric or neurological disorders were recruited via public and institutional participant pools, of which 43 were included in the final data set (16 male, average 31 years, ± 10.6 SD). All participants had normal or corrected-to-normal vision and were naïve to the purpose of the experiment. Upon completion, participants received a monetary reward of 20€. The experiment was created using PsychoPy (version 2020.1.3).[44] Participants were asked to indicate the global motion direction of RDKs, which was either left or right on the horizontal axis. There were six levels of discriminability, determined by the proportion of coherently moving dots. To induce high-level beliefs about the stimulus, an auditory cue preceded stimulus presentation. The cue accurately predicted the RDK's global motion direction in 75% of trials. The experiment consisted of 8 blocks (96 trials per block, 768 total). There were two types of blocks. In neutral (N-type) blocks, the stimulus' global motion direction was selected randomly. In repetitive (R-type) blocks, the motion direction in trial *t-1* was repeated in 80% of subsequent trials *t*, increasing the relevance of low-level prior information. There were two possible block sequences, NRRNRNNR or RNNRNRRN, which were counterbalanced across participants. In a subset of fourteen participants, the block sequences differed slightly (counterbalanced NRNRNRNR or RNRNRNRN), which we accounted for in our statistical analysis. Upon completion, participants received global feedback about their performance, were informed about the true level of cue accuracy, and completed a short debriefing questionnaire.

2.3 Questionnaires

After the experimental tasks of both *Experiment 1* and *2*, participants completed two validated questionnaires measuring psychosis proneness, the Peters et al. Delusions Inventory, PDI[45], and the Cardiff Anomalous Perceptions Scale, CAPS[46]. A global psychosis-proneness score (PPS) per subject was calculated by summing the global z-transformed CAPS- and PDI sum scores. Considering usually high correlations between CAPS and PDI scores[8], our main analyses utilized this global PPS. To elucidate the contributions of delusion- and hallucination proneness separately, we performed additional exploratory analyses on PDI- and CAPS scores, respectively (**S4**).

2.4 Statistical analyses

Behavioural data were analysed with a mixed logistic regression model. The model was fit using R[47] (version 4.1.1), the lmer4 package[48] (version 1.1-27.1), using maximum likelihood and the optimx package[49] (v. 2021-10.12), with method nlminb for quadratic optimization. Explained variance or R^2 was computed using the MuMIn package[50] (version 1.43.17). Variance Inflation factors (VIF) were computed using the car library (v.3.0-12). The logistic model was defined as (R-style notation):

$$r_t = s_t + s_{t-1} + d_t + r_{t-1} * PPS * blocktype + c_t * PPS * blocktype \underline{+ (1|subject) + (1|block{:}subject)} \qquad (1)$$

The dependent variable was the choice (or response) in trial t (r_t, 0=right, 1=left). Considered predictors were the current (s_t) and previous (s_{t-1}) stimulus (0=right, 1=left), discriminability (d_t; Δclicks (1-6) in *Experiment 1* and coherence levels (0.005-0.5) in *Experiment 2*), block type (*blocktype*, where 0=repetitive, 1=neutral blocks), the current cue (c_t, 0=right, 1=left) and psychosis proneness (*PPS*). Interactions were defined along our hypotheses: an interaction of previous choice and *PPS* (low-level prior effect) and an interaction of cue and *PPS* (compensatory high-level prior effect), while considering the influence of the block statistics (i.e., *blocktype*). Note that we focused our analyses of choice history on the immediately preceding choice (i.e., r_{t-1}), which has been found to exert the strongest bias.[21,25,51] To illustrate choice history effects and their adaptation to block statistics, we fitted psychometric functions of the form:

$$p(r = 1) = \frac{1}{1 + exp\left(\frac{\pi(x-\delta)}{\sqrt{3}\sigma}\right)} \qquad (2)$$

We assumed a logistic noise distribution with variance $\frac{s^2\pi^2}{3}$ where σ is the standard deviation of the assumed logistic noise distribution and captures decision noise. δ is a systematic bias towards right (r=0, δ >0) or left (r=1, δ<1) choices, and x represents the stimulus variable. We split the data with respect to the previous choice and fit two psychometric functions representing trials preceded by ”left” or ”right” choices, respectively.

To further illustrate the relationship between choice history and psychosis, we analysed the correlation between individual PPS and the tendency of individuals to repeat the previous choice (repetition probability). The mean repetition probability per individual was given by summing over all instances of choice repetitions and dividing by the total number of trials T. Subject-specific repetition probabilities were correlated with PPS.[14,18]

3 Results

In *Experiment 1*, participants performed perceptual decisions on auditory stimuli in an online, gamified 2AFC task.

On average, task performance was at 80.1% correct responses (± 7.1 SD), ranging from 61.2% to 89.8%. 2.1% of trials timed out (response time >2500ms) and were excluded from further analyses.

Mean PDI sum score was 6.6 (± 3.1 standard deviation), with sum scores ranging from 0 to 17. Mean CAPS score was 6.5 (± 5.2 standard deviation), with sum scores ranging from 0 to 28. CAPS and PDI scores were strongly correlated (r=0.71, p <0.001, Table **1**, for details, see **S2**).

In *Experiment 2*, participants made decisions on RDK stimuli with 71.9% average accuracy (± 5.0 SD). Performance levels ranged from 65.5% to 79.3% correct choices. Less than 1% of trials timed out (response time >2500ms) and were excluded from further analyses.

Mean CAPS score was 5.0 (± 5.2 SD), and mean PDI score was 7.3 (± 6.9 SD). CAPS sum scores ranged from 0 to 20; PDI sum scores ranged from 0 to 35. CAPS and PDI scores were strongly correlated (r=0.82, p <0.001, **S2**).

We fit separate trial-by-trial logistic mixed regression models for both experimental datasets. The logistic choice model allowed us to estimate the influence of e.g. stimulus, cue and previous trial events and their interactions with PPS on current choice. Residuals were normally distributed in both *Experiment 1* (scaled residuals, *min*=-3.66, *max*=3.55, 1*Q*=-0.50, 3*Q*=0.50; number of observations=42,601) and *Experiment 2* model fits (scaled residuals, *min*=-4.19, *max*=3.24, 1*Q*=-0.62, 3*Q*=0.63, number of observations=31,087). Marginal corrected R^2 values were R^2=0.40 for *Experiment 1* and R^2=0.32 for *Experiment 2*. Maximum VIF in *Experiment 1* was VIF=1.33 (previous stimulus), in *Experiment 2,* it was VIF=1.67 (previous stimulus), indicating no significant problems with collinearity.

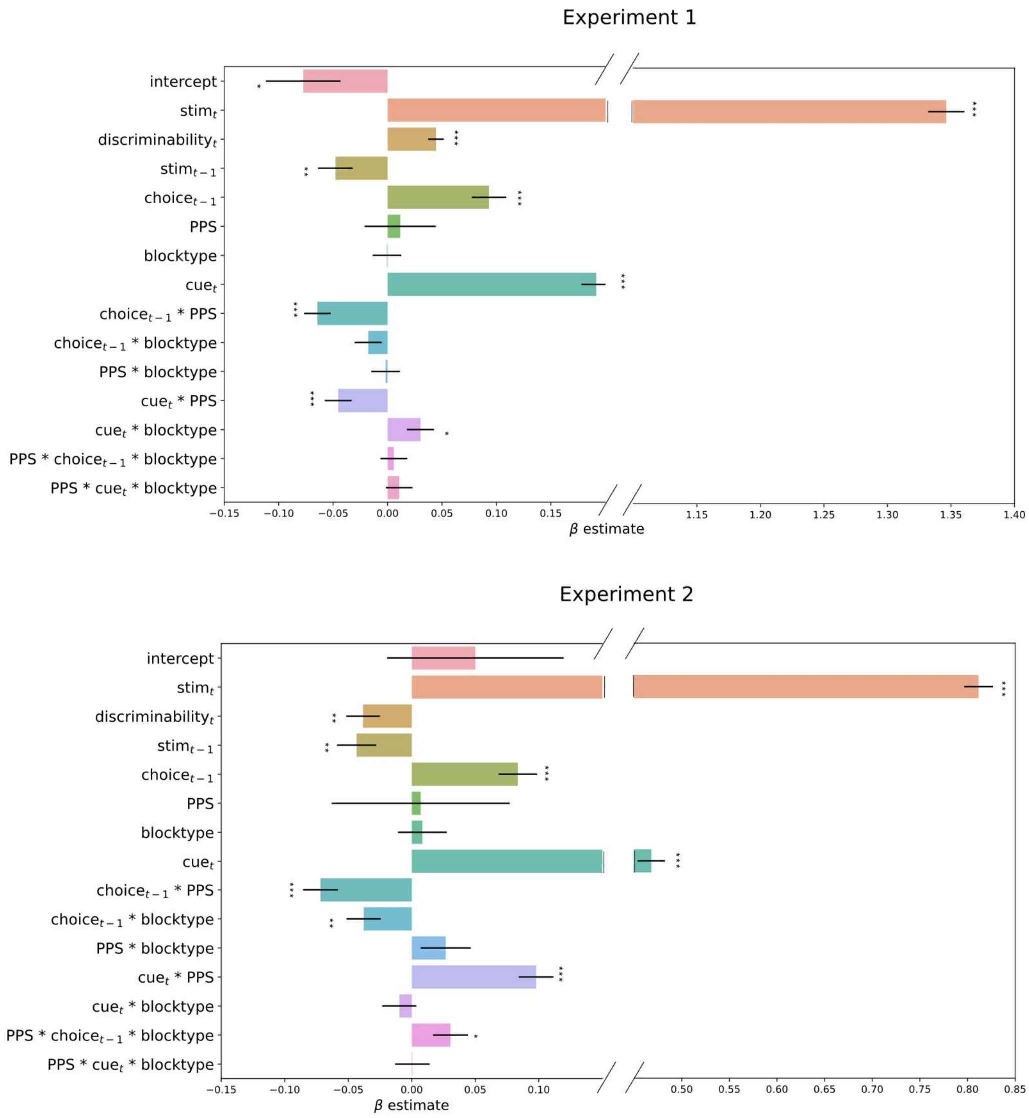

Figure 1: Coefficients of the logistic choice model. **A** *Experiment 1*. **B** *Experiment 2*. Coloured bars: coefficient estimates, black lines: standard errors. $stim_t$/ $stim_{t-1}$: (previous) stimulus, PPS: psychosis proneness score

	Age	Performance	PDI	CAPS
Experiment 1	24.79 ± 7.34	80.1% ± 7.1	6.6 ± 3.1 (range: 0-17)	6.5 ± 5.2 (range 0-28)
Experiment 2	31.0 ± 10.6	71.9% ± 5.0	7.3 ± 6.9 (range 0-35)	5.0 ± 5.2 (range 0-20)

Table 1. Distribution of age and psychosis proneness scores (mean ± standard deviation) across experiments.

3.1. Choice history biases in perceptual decision-making

We found a significant main effect of previous choice in *Experiment 1* and *Experiment 2* (see also Figure **1**; *Experiment 1:* β=0.09 ± 0.01, p<0.001; *Experiment 2:* β=0.08 ± 0.02, p <0.001). The general effect of previous choice is visible as a horizontal offset between psychometric functions fitted on previous-left versus previous-right choices (Figure **2**).

The choice history bias was stronger in repetitive (coded 0) versus neutral (coded 1) blocks in *Experiment 2*, as indicated by a significant interaction between previous choice and block type (*Experiment 2*: β=-0.04 ± 0.01, p =0.005, compare function offsets in Figure **2**). Thus, participants' choice history biases adapted to the trial structure. This effect did not reach significance in *Experiment 1* (β=-0.02 ± 0.01, p=0.15).

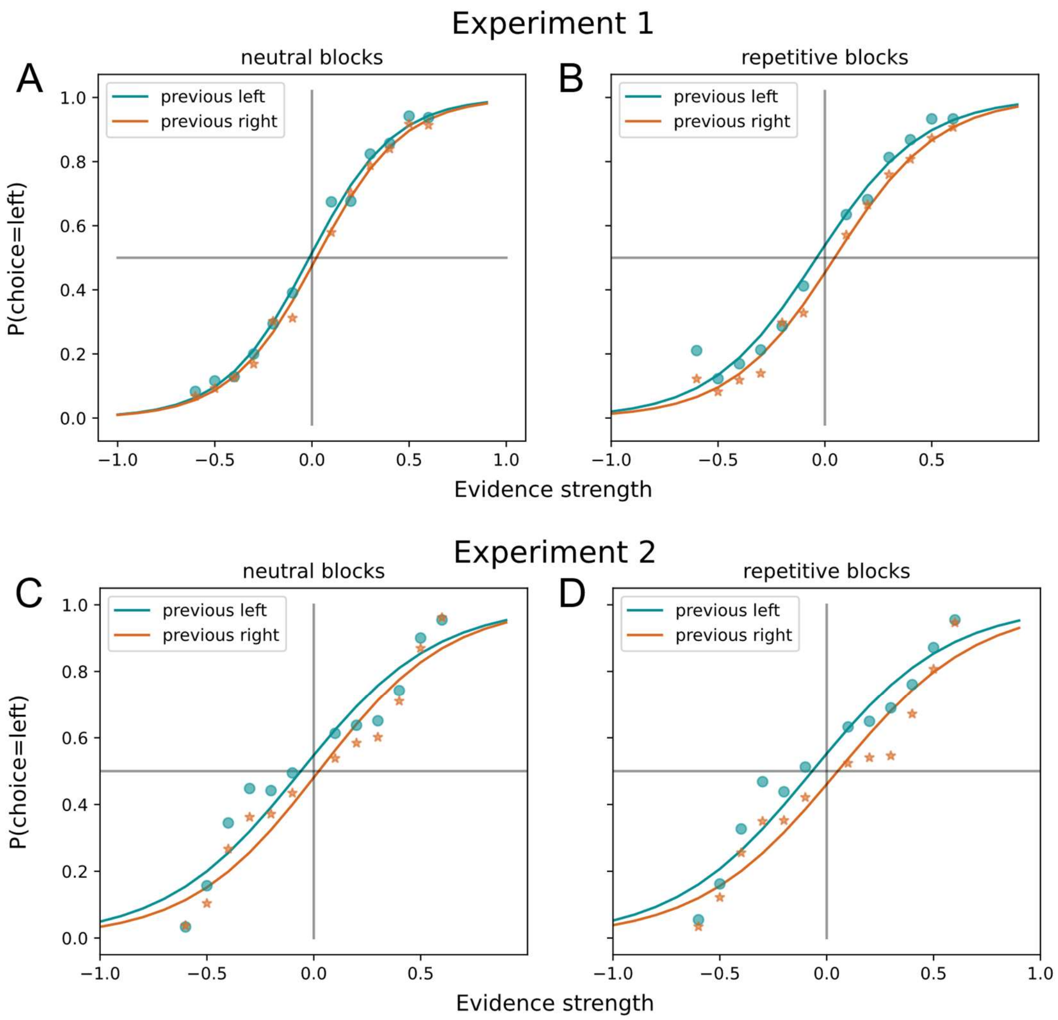

Figure 2: Psychometric functions conditional on previous choices

Psychometric functions showing the probability of a ”left” choice, separately for trials preceded by ”left” (turquoise) and ”right” (orange) choices. Markers represent averaged data per discriminability level.

3.2. Choice history biases decrease with psychosis proneness

In line with our main hypothesis, the logistic choice model revealed a significant interaction between PPS and previous choice in both experiments (*Experiment 1*: β=-0.06 ± 0.01, p <0.001; *Experiment 2*: β=-0.07 ± 0.01, p <0.001). The negative weight indicates decreasing choice history biases with increasing PPS. The relationship between participant-specific choice repetition probabilities and PPS is further illustrated in Figure **3**. It held across both neutral (Figures **3B, E**) and repetitive blocks (Figures **3C, F**) in both experiments. We further found robust interactions between individual CAPS- and PDI scores and choice history (**S4**).

The three-way interaction between choice history, PPS and block type was indistinguishable from zero in *Experiment 1* (β=0.005 ± 0.01; p = 0.64), but marginally significant in *Experiment 2* (β=0.03 ± 0.01, p = 0.02). The latter result indicates that the negative choice history * PPS interaction was more pronounced in blocks with a repetitive stimulus structure.

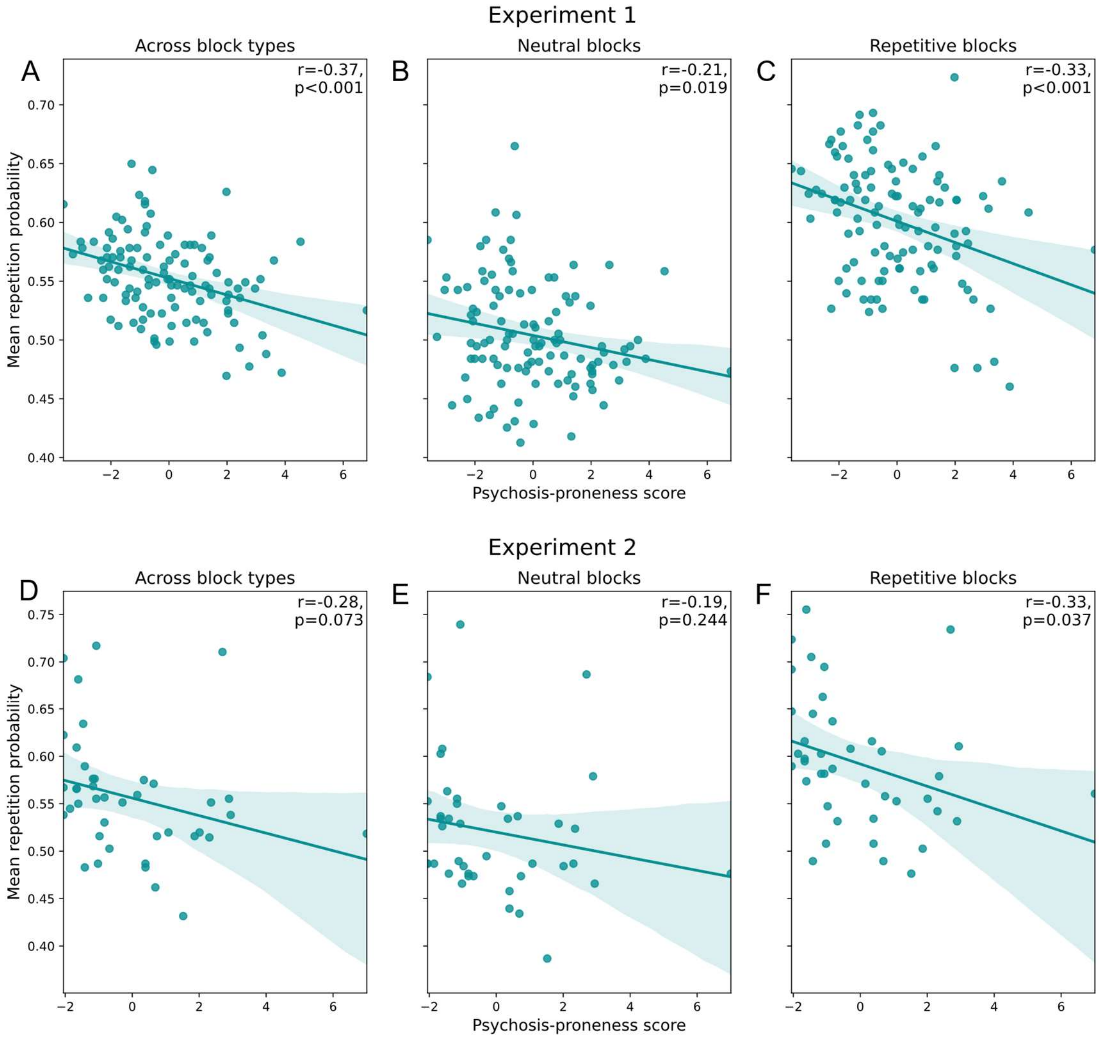

Figure 3: Repetition probability decreases with PPS.

A-C *Experiment 1*. (**A**) across block types, (**B**) neutral blocks, (**C**) repetitive blocks.
D-F *Experiment 2*, across block types (**D**), for neutral (**E**), and repetitive blocks (**F**).

3.3. Psychosis proneness and high-level prior beliefs

Finally, we tested our exploratory hypothesis that a decreased utilization of low-level priors in psychosis-prone individuals is, at least in part, compensated by an increased reliance on high-level priors. We confirmed that the cue exerted a significant main effect on perceptual choices in both experiments (see also **S3** and **S6;** *Experiment 1*: $\beta=0.19 \pm 0.01$, $p < 0.001$; *Experiment 2*: $\beta=0.47 \pm 0.01$, $p < 0.001$). The interaction effect between cue effects and PPS was not consistent between experiments. In *Experiment 1,* the interaction was negative ($\beta=-0.04 \pm 0.01$, $p < 0.001$). Thus, contrary to our hypothesis, we here found reduced reliance on high-level priors in individuals with higher psychosis proneness. In contrast, *Experiment 2* yielded a positive interaction between cue effects and PPS ($\beta=0.10 \pm 0.02$, $p < 0.001$). When examining the interactions between cue and PDI and CAPS scores separately, we found that cue reliance was modulated by PDI scores in both experiments, albeit in opposite directions. The interaction of cue and CAPS scores did not generalize across experiments (**S4**). Results are hence inconsistent across experiments and measures. The interaction between cue and PPS was not significantly modulated by block type across experiments.

4 Discussion

In the present work, we examined how the reliance on prior information varied with psychosis proneness in visual and auditory decision-making. Choice history, as a proxy for low-level perceptual priors, significantly influenced perceptual decision-making and adapted to statistical regularities in stimulus sequences in the visual modality. Supporting our main hypothesis, choice history biases decreased with increasing psychosis proneness across modalities. The negative relationship between psychosis proneness and choice history was stronger in repetitive blocks and thus a setting in which the build-up of low-level priors was adaptive (significantly so only in the visual modality). Finally, we explored the impact of higher-level information on perceptual decision making but found no conclusive evidence for a consistent effect of psychosis proneness.

Overall, we found robust evidence for our main hypothesis of reduced choice history biases in psychosis proneness, which generalized across perceptual modalities, experimental settings and environmental statistics. This finding is in line with the predictive processing account of psychosis, according to which reduced perceptual priors lead to insufficiently constrained internal models.[4,7,10,11] Considering delusion- and hallucination-proneness separately, we found that choice history was modulated by both. This suggests that delusions and hallucinations share common underlying mechanism, rooted in aberrant perceptual inference.

While increasing the relevance of the low-level prior through a repetitive stimulus sequence led to generally stronger choice history biases, only in *Experiment 2* was such adaptation to block statistics significantly related to psychosis proneness. Thus, we provide partial evidence that a reduced reliance on low-level priors in psychosis prone individuals is more pronounced when increasing the relevance and adaptive nature of such low-level priors.

Regarding our hypothesis of a compensatory increase in the reliance on high-level prior information[7,10,18], we found conflicting evidence in *Experiments 1* and *2*. In *Experiment 1*, reliance on cues decreased in more psychosis prone individuals, while in *Experiment 2*, it increased with psychosis proneness. This inconsistency may be due to the difference between the cues across experiments: in *Experiment 1, visual* cues were implemented to induce high-level beliefs about auditory stimuli, while in *Experiment 2*, *auditory* cues were implemented to induce beliefs about visual stimuli. It is possible that the auditory cue in *Experiment 2* was more salient. Also, reduced attentional levels in the online setting cannot be ruled out. This may have been especially true in more psychosis prone participants, leading to a decrease in cue reliance in *Experiment 1.* Overall, the inconsistencies between the two experiments in our study precludes strong conclusions regarding the hypothesized over-reliance on high-level priors in psychosis-prone individuals.

It should be noted that our trial-wise manipulation of high-level prior information through cross-modal, explicit cues differed from previous studies that had pointed to strong priors in psychosis. Powers et al.[17] found that expectations that were learned over time had an increased influence on perception in hallucinating individuals. Possibly, if our tasks had involved learning of cue-stimulus associations over time, more psychosis prone individuals might similarly have shown stronger reliance on these cues. Schmack and colleagues[14] manipulated high-level priors by inducing abstract beliefs about the effect of viewing glasses in a placebo-like manner and found an increased influence of these beliefs on perception in psychosis-prone individuals. Others have manipulated high-level priors by varying semantic context[52] or learned letter-sound associations[53]. In contrast to these manipulations, trial-wise cues as those used in our study operate on much shorter timescales. Still, the cross-modal cues used in our experiments can be regarded as high-level information as they provide explicit cognitive information (i.e., probability of the next percept) and require integration at a higher modality-independent level of the processing hierarchy. However, the hypothesized over-reliance on high-level information in psychosis-proneness may require the build-up of priors at longer timescales. The relevance of different types of high-level priors for delusions and psychosis therefore needs further investigation.

The main finding of decreasing choice history biases in psychosis proneness extends recent work by Stein and colleagues in patients with schizophrenia and anti-NMDAr-encephalitis. Both patient groups showed drastically decreased effects of trial history in a spatial working memory task compared to controls.[29] In the case of acute anti-NMDAr-encephalitis, choice history effects normalized with recovery, suggesting the importance of NMDAr for both psychosis and trial history effects. In combination with our findings in non-clinical samples, this suggests that reduced weighting of sensory priors in perceptual information processing may represent a trait marker predisposing for psychotic experiences.[29]

While we consider the generalization of our main hypothesis across modalities and experimental settings as a strength, this heterogeneity may have been a limiting factor for the investigation of high-level prior effects. In particular, *Experiment 1* was performed as an online study, which may lead to concerns regarding data quality.[52,53] Therefore, we implemented several measures to rigorously assure data quality, such as a headphone test and random attention checks. Additionally, there was a difference in performance levels: the auditory task of *Experiment 1* was easier than the visual task of *Experiment 2*. Therefore, the effect of the predictive cue and the adaptation of choice history biases to block statistics was more reliably detected in the visual experiment. Future research should control for task performance, e.g. via adaptive staircasing procedures, when investigating these effects in the auditory modality.

Overall, our results support the notion of decreased low-level priors as a trait marker of psychosis. This seems to hold for both diagnosed patients with schizophrenia[29] and across the psychosis spectrum more generally. Further investigations of choice history biases in other diagnostic groups frequently reporting psychotic experiences, such as bipolar disorder, Parkinson's-or Alzheimer's disease, will clarify whether the reduced weighting of low-level priors is a general mechanism underlying psychotic experiences beyond diagnostic categories.

Additionally, computational modelling may provide fruitful avenues towards an improved understanding of perceptual inference in psychosis.[7,10,54] Specifically, Bayesian models of perception may help to explicitly model priors, hidden states and precision estimates and their relationship to psychosis proneness.[55] While the application of such Bayesian modelling approaches is an interesting avenue for future research, it is beyond the scope of the present study, which was optimized for quantifying choice history effects and their modulation by psychosis proneness. Similarly, modelling of evidence accumulation, e.g. using drift diffusion models, may elucidate the mechanisms underlying aberrant perceptual decision-making in more psychosis prone individuals.[56] However, the use of drift diffusion modelling was beyond the scope of the current study, especially as we did not collect the necessary reaction time data.

An open question relates to the neural underpinnings of reduced choice history biases in clinical and subclinical psychosis. Previous neuroimaging studies in healthy controls have indicated a critical role of early visual cortex V1 for visual serial dependency effects.[57] It is unclear how these findings translate to other perceptual modalities and how they relate to altered perceptual inference in psychosis. To discern subtle aberrancies regarding low-level and high-level prior beliefs, as well as a sharpened precision of sensory feedforward signals, future studies may use layer-specific neuroimaging to constrain predictive processing models of psychosis.[4,58,59]

In conclusion, the present work provides cross-modal evidence for decreased choice history biases in individuals prone to psychotic experiences. The hypothesized compensatory mechanisms of an increased reliance on high-level priors was not supported across modalities. Taken together, our results emphasize the notion of a reduced influence of low-level perceptual priors in perceptual inference as a hallmark of psychotic experience.

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6 Data availability

Scripts and data are available at https://github.com/Eckertal/ChoiceHistPsych

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Supplementary Materials

Cross-domain evidence for decreased choice history biases in psychosis prone individuals

PsyArXiv pre-print

Contents

S1. Experimental procedures

We here describe the experimental procedures, apparatus, and stimuli as well as the exclusions and participants of *Experiments 1* and *2* in more detail.

S1.1. Experiment 1

Participants. *Experiment 1* (N=113) was an online, gamified auditory perceptual decision-making task (compare [1]). The experiment was opened for 150 participants via the online recruitment platform prolific.[2] Two datasets were lost due to technical problems. As stated in our pre-registration, a participant was included in subsequent data analysis when their performance fell between 60% and 90%. Twenty-nine participants were excluded based on their performance, with fourteen participants underperforming (<60% correct choices), and fifteen participants performing at ceiling levels (>90% correct choices). Participants who failed to respond correctly in less than 60% of trials were excluded from further analyses because their behaviour might have been random (guessing probability of 50%). Performance at ceiling levels (>90% correct) was considered prohibitive to the analysis of choice history biases.[3] Twenty-nine participants were excluded based on their performance. Fifteen subjects' performance was too high (>90%) and 14 subjects' performance was below 60%.

Given they passed the required number of attention checks, over- and under-performers were paid for their participation, even though their data were not further considered here. Of the poor performers, two failed to pass the required number of attention checks, which speaks for inactivity during the experiment, and therefore did not receive monetary reward. In general, 81% of participants (120 out of 148) passed 25 or 26 out of 26 attention checks. All included participants passed more than the required 20 attention checks.

Six participants did not finish the questionnaires before the experiment timed out at 1 hour and 30 minutes. Here, questionnaire data for the psychosis-measures were either incomplete or missing. These participants were compensated, but their data were not considered in the main analysis. 113 participants were included in the final data set (75 male, mean age 24.7± 7.34 years; mean Prolific score[2]: 99.4/100, average number of submissions: 199.2).

The sample size of 150 subjects was calculated a priori, based upon prior work of our group into psychosis-proneness.[4] However, these studies relied on laboratory-based experiments in the visual domain. Power calculations yielded that 110 subjects can discover a small effect in $R^2 = 0.10$ in a regression model with 4 predictors with a power of 0.8. Assuming overall poorer data quality and a higher proportion of exclusions, potential technical failures and performance-based requirements for the analysis of history effects, another 40 participants were considered in this calculation.

Apparatus and stimuli. The experimental procedure was created using the Gorilla online task builder for visual online experiments, augmented with custom JavaScript code.[5] Participants' end devices were restricted to either a desktop or laptop computer; users of mobile devices such as smartphones or tablets were not forwarded to the experimental part. The participants' screen size ranged from 600 to 2560 pixels in width and from 600 to 1440 pixels in height. Accepted browsers were Chrome, Firefox, Safari or Microsoft Edge in order to minimize browser-related timing variability.[6] Participants were instructed to wear functioning headphones and to complete the experiment in a quiet and undisturbed room. As a first step, participants were asked to adjust the volume of their headphones. They were required to adjust sound volume via a sliding bar until the headphones were set on a volume that was comfortable and clearly discernible while white noise was played. The participants' technical set-up and environment was tested using a headphone check.[7] Here, participants were presented with a sequence of three tones. Participants were asked to indicate which of the three tones had the lowest volume. These tones were not detectable using the computer's loudspeakers or when completing the test in a loud environment. If participants failed two out of six trials, they were not forwarded to the experimental part of the study, ensuring only participants with functioning headphones in a quiet environment participated.

The experimental task was gamified to increase participants' engagement.[8] The participants' role was to judge two typewriting competitors. Two figures, named Grace and Mark, were presented in an office-like environment at a desk left and right to centre, respectively. The left and right speakers of the participants' headphones corresponded to the left and right desk, respectively. Participants were informed that Grace is usually typing faster than Mark. As an example, it follows that participants should expect to hear more clicks on the left ear when Grace appeared on the left desk. The cue was implemented to induce higher-level prior beliefs about the auditory stimulus.

Each trial started with a short perturbation during which an ”empty office” was presented (pre-cue jittered interval, mean duration 750ms +/- 500ms). Subsequently, the cue figures Grace and Mark appeared on the right and left side of the screen in a counterbalanced manner for 750ms. The figures appeared on equally often on both sides to not induce biases towards one side. This cue was indicative of the dominant side, i.e. the ear to which more clicks were presented, subsequently referred to as the "target ear", with 75% accuracy. The visual cue was followed by a jittered pause in which the empty office was presented ("empty office", mean duration 750ms +/- 500ms). The auditory stimulus had a duration of 2500ms and consisted of a train of 40 click-sounds in total. Different proportions of these clicks were presented to each ear, with, for example, 21 clicks presented to the left and 19 clicks presented to the right ear, in the case of the most difficult stimulus. There were six levels of discriminability (19-21, 18-22, 17-23, 16-24, 15-25, 14-26). There were equal numbers of left and right stimulus trials for all discriminability levels. The click sequences were custom-generated using Python and individual click sounds were spaced so that they a) did not overlap and b) the complete stimulus duration was 2500ms. Participants were prompted to give their response after the offset of the auditory stimulus ("More clicks on the...") by selecting one of two boxes saying either "left" or "right" with a mouse click. The boxes were arranged on a vertical and central axis below the fixation cross and the position of each the boxes ("left" or "right") was orthogonalized trial-wise. Participants were required to give their choices within 2000ms, otherwise the experiment advanced to the next trial and the response was recorded as "missing". Participants completed a short training block to get acquainted with the task. The experiment then consisted of 8 blocks with 48 trials each, resulting in 384 trials in total (approximately 45 minutes duration). There were two types of blocks. In N-type (or neutral) blocks, the target ear was chosen randomly in each trial. In R-type (or repetitive) blocks, the target ear of trial t − 1 was repeated in trial t in 80% of cases. Block sequences followed one of two possible patterns, NRRNRNNR or RNNRNRRN, which were counterbalanced across participants. Twenty-six attention checks were placed randomly within the blocks. They consisted of a computerized voice prompting participants to press a specific key on their keyboard (e.g. "Press O"), paired with the prompt on screen: "Please press requested key". Participants had 3500ms to press the requested key. Out of 26 attention checks, participants had to detect and correctly respond to 20, otherwise their data were discarded. After each block, participants were encouraged to take a break which was limited to one minute. A countdown was displayed for the last 10 seconds of the break, after which the next block started in the participant did not proceed by button press before. Participants were instructed to check whether they wore their headphones correctly prior to the experimental part and after the breaks (i.e., with the side marked with an 'L' on the left ear). Upon completing all eight blocks, participants were informed about the true level of cue correctness (75%) and received a global feedback about their performance (correct responses per block in percent). A short debriefing questionnaire asked the participant whether any distractions or technical disturbances had occurred during the experiment, their level of concentration and their overall strategy when responding to the task as open questions.

S2.2 Experiment 2

Participants. *Experiment 2* was a laboratory-based visual decision-making task using random dot kinematograms (RDKs). Experimental procedures were in line with the Declaration of Helsinki and all participants gave written informed consent before participating. Fifty healthy participants without a history of psychiatric or neurological disorders were recruited via advertisements in a public online market place and via an institutional study recruitment platform located at the Humboldt-Universität zu Berlin. A sample size of 50 participants was calculated a priori, based on similar studies[4,9] and a power analysis, where the power was set to 0.8, an α=0.05, a small effect size of type R^2 and an effect size value of 0.2.

Two participants were excluded based on their performance. None of the participants performed at ceiling levels in this task (>90% correct responses), but the performance of two participants was too low (<60% correct responses). Of the remaining 48 participants, seven gave incomplete survey responses, ended the experiment prematurely or refused to respond to either one or both surveys measuring psychosis - proneness. Their data were not included in the final data set, leaving a total sample size of 41 after exclusions (16 male, average 31 years, ± 10.6 standard deviation).

Apparatus and stimuli. Participants were seated in a dimly lit, quiet room. They rested their chins on a headrest fixed at a 30cm distance from a Fujitsu computer-monitor (50.8 cm x 28.7 cm) and were instructed to maintain fixation during the experiment. The experiment consisted of 8 blocks (96 trials per block, 768 trials in total). Participants were encouraged to take self-timed breaks after each block. They were provided with a small snack and drink to be consumed exclusively during the breaks.

A trial started with a brief fixation period of 200 ms, followed by an auditory cue. A red bull's eye fixation cross (30 x 30 pixels) was presented at the centre of the screen for the entire duration of the trial. The auditory cue was a female, computerized voice saying the words "left" or "right" (duration: 625 ms). Participants received written instruction that "the voice was correct about the global direction of the moving dots in most cases, but not always". Analogous to the typewriting competitors in *Experiment 1*, the cue was accurate in 75% of trials and implemented to induce a higher-level prior belief about the subsequent visual stimulus. After a jittered pause of 750-1000 ms, a RDK consisting of 200 white moving dots appeared. The dots were sized at 3 pixels and moved at 0.07 pixels per frame. The dots' lifetime was 15 frames, after which they were re-positioned randomly and non-overlapping with other dots. The same applied to dots leaving the stimulus field before reaching the end of their lifetime. The total size of the circular field was 22 visual degrees. There were two possible motion directions: left and right on the horizontal, central axis. There were six levels of discriminability, following the method of constant stimuli: 0.05, 1.62, 3.15, 7.92, 19.91 and 50%, which has resulted in performance levels of approximately 70% correct in previous studies.[9,10] The response screen consisted of a prompt to report the global motion direction ("Direction?") and two black arrows, arranged on the central, vertical axis, pointing either to the left or to the right side of the screen. The leftward- and rightward-pointing arrows switched position randomly on each trial to avoid motor repetition artifacts. Trials were temporally separated by a jittered intertrial interval (ITI) of 750-1000 ms. Equivalent to *Experiment 1*, there were two types of blocks. In neutral (N-type) blocks, the global motion direction of the stimulus was selected randomly. In repetitive (R-type) blocks, the global motion direction of trial $t-1$ was repeated in trial t with a chance of 80%, while the opposite direction was presented in only 20% of cases. This led to prolonged phases of left- or rightward moving stimuli. There were two possible block sequences, NRRNRNNR or RNNRNRRN, which were counterbalanced across participants. In a subset of fourteen pilot participants, the block sequences differed slightly (counterbalanced either NRNRNRNR or RNRNRNRN).

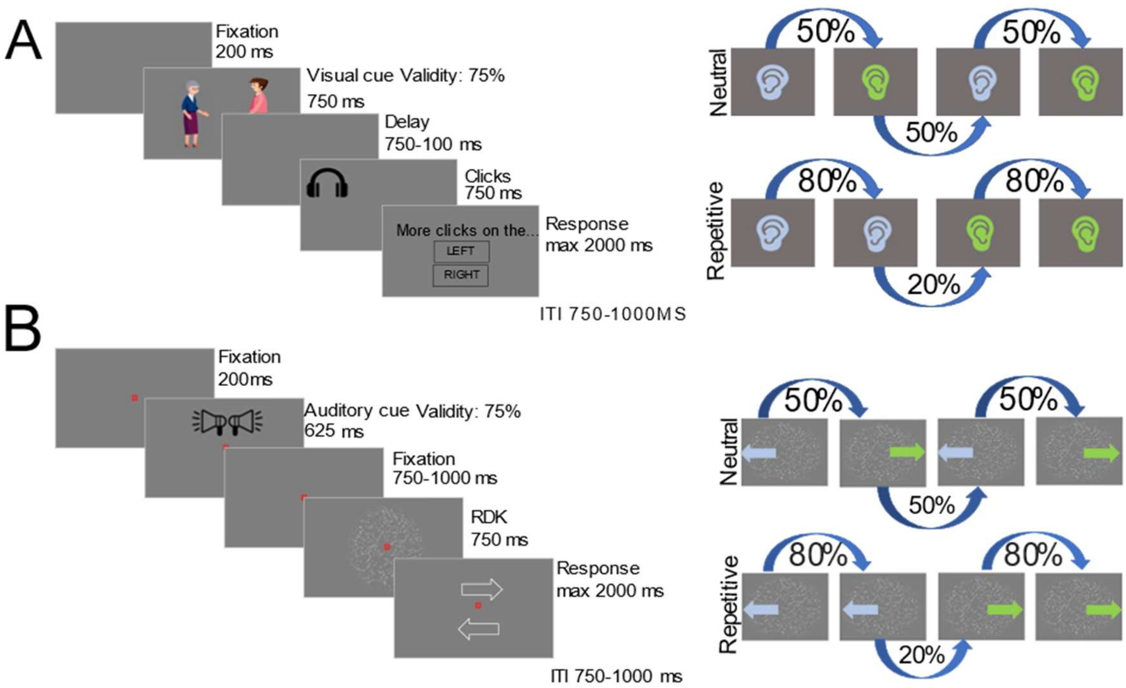

Figure S1: Behavioural tasks of Experiments 1 and 2.

A. Each trial started with the presentation of a visual cue inducing an expectation for left- or right-ear target with 75% accuracy (high-level prior). Subsequently, participants had to judge whether more click sounds were presented to the left or the right ear. In neutral blocks, the target ear was selected randomly in each trial. In repetitive blocks, the target ear was repeated with a probability of 80%, leading to prolonged phases of left- or right-ear stimulus trials.

B. In Experiment 2, a trial started with an auditory cue, which predicted with 75% accuracy the global motion direction (left- or rightward) of a subsequent random dot kinematogram (RDK). Motion direction was selected randomly in neutral blocks. In repetitive blocks, the repetition probability was 80%, leading to prolonged phases of leftward- or rightward-moving RDKs.

S2. Sample characteristics

In the following, we describe the distribution of psychosis proneness scores of both experiments in more detail. Figure **S2** visualizes the distribution of raw PDI- and CAPS scores (*Experiment 1:* **S2.A-C**, *Experiment 2:* **S2.D-F**).

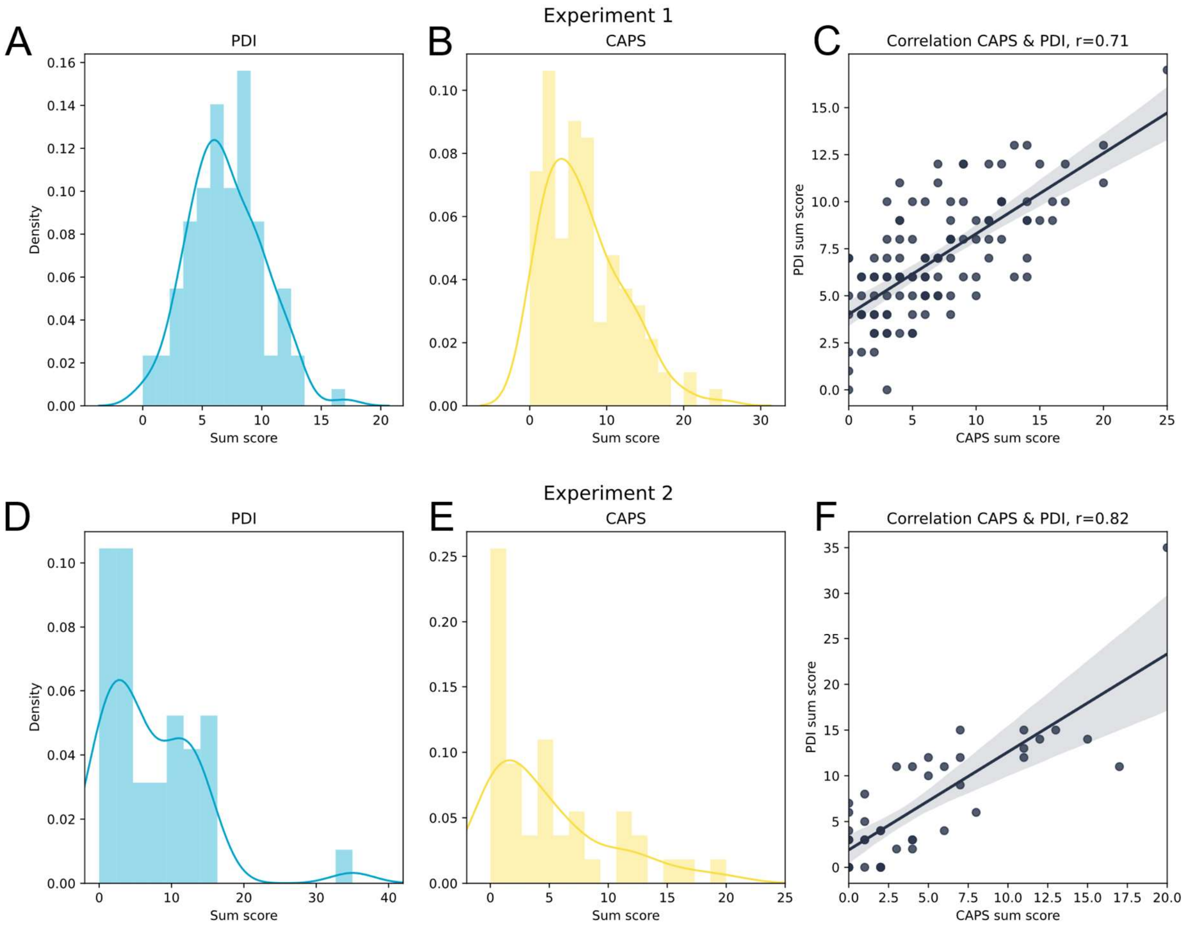

Figure S2.1: Distribution of psychosis proneness scores across the experiments

S3. Logistic model and test cases

Detailed information on regression coefficients of the full logistic choice model is displayed in **Table S3.1** for *Experiment 1* and **Table S3.2** for *Experiment 2* (for a visualization, see main **Fig. 1**).

1. Test models

To investigate the effects of our manipulations in the model in more detail, we further implemented some simpler models to probe our manipulations of block structure and cue. Our first model predicts current choice from the current trial's stimulus (s)- and cue (c) identities. A random intercept for subject is added, resulting in the following regression model:

$$r_t \;=\; (1|subject) + s_t \;+\; c_t \tag{S3.1}$$

In the second test model, current choice is predicted from stimulus category and block structure. We also investigated the interaction of block structure with choice history in this test model. This requires adding also the previous stimulus variable to the equation, giving the following model definition:

$$r_t \;=\; (1|subject) + \; s_t \; + s_{t-1} + \; blocktype_t \; * \; r_{t-1} \tag{S3.2}$$

A third test model considered the interaction between the previous trial's discriminability with choice history, such that:

$$r_t = (1|subject) + \; s_t + \; s_{t-1} + \; r_{t-1} * \; d_{t-1} \tag{S3.3}$$

Regarding the first model (eq. **S**3.**1**), cue had a positive and significant main effect on current choice beyond stimulus in both experiments (see Tables **S3.3, S3.4**). Block type did not exert a significant main effect on current choice across experiments, and interacted significantly with the effects of previous choice only in *Experiment 2.* Previous choice exerted a significant and positive main effect on current choice across both experiments. From the third test model (eq. **S3.3**), there was evidence for a significant main effect of choice history in *Experiment 2* only; when entered in interaction with preceding trial discriminability, the main effect of choice history did not reach significance. In both models, choice history interacted significantly with the preceding trial's difficulty. In this model, the main effect of previous choice is interpreted as the effect of choice history when discriminability = 0, indicating a slight tendency to alternate between choice options across both studies (negative β, significant only in *Experiment 2*). The tendency to alternate decreases with discriminability in *Experiment 1.* In *Experiment 2,* a negative interaction between choice history and previous discriminability indicates that choice history effects increase for low previous discriminability. In conclusion, results of these test models suggest that cue and stimulus exert the expected effects on current choice across experiments. The block type manipulation, however, seems to have been effective only in the experiment in the visual modality. A previous study suggested that choice history biases adapt to block statistics in the visual modality[9], which we replicate in the visual, but not in the auditory modality. Finally, the previous trial's discriminability interacts with choice history effects. At minimal discriminability levels, choices tend to alternate more in *Experiment 1*, whereas in *Experiment 2,* this effect was reversed such that a positive effect of choice history emerged for low discriminability. These effects point towards differential modulation of choice history by stimulus discriminability in the auditory vs. visual domain, an incidental finding which necessitates further research.

With an additional test model, we investigated the effects of motor response. Motor repetition is an alternative explanation for choice history biases which we addressed in our experimental paradigm by randomizing stimulus-response mappings on each trial. However, a further test model of the shape

$$r_t = (1|subject) + (1|block{:}subject) + s_t + d_t + s_{t-1} + c_t * PPS * blocktype_t + r_{t-1} * PPS * blocktype_t + m_{t-1} * PPS, \tag{S3.5}$$

where m_{t-1} represents the previous motor response, or the identity of the button pressed on the previous trial, was implemented. Regression results are summarized in Tables **S3.5** and **S3.6.** Previous motor response exerted a small, marginally significant main effect on current choice in *Experiment 1.* Here, the interaction between psychosis proneness and previous motor response reached marginal significance as well. The effect of interest (i.e. PPS * r_{t-1}), however, remained highly significant. In *Experiment 2,* neither a main effect of previous motor response, nor a significant interaction between previous motor response and psychosis proneness score was observed.

Finally, we implemented a version of the test model in which stimulus history was not considered in addition to choice history. The regression model is given by

$$r_t = (1|subject) + (1|block\colon subject) + s_t + d_t + c_t * PPS * blocktype_t + r_{t-1} * PPS * blocktype_t$$

(S3.6)

Importantly, the main interaction of interest between psychosis proneness and choice history remains significant. This indicates that our result is not a spurious effect caused by controlling for stimulus history.

Variable	β	SE	z	p	sig.
Intercept	-0.08	0.03	-2.26	0.03	*
Stimulus	1.34	0.01	93.93	< 0.001	***
Discriminability	0.04	0.01	6.16	<0.001	***
Previous stimulus	-0.05	0.02	-2.99	0.002	**
Previous choice	0.09	0.02	5.90	<0.001	***
PPS	0.01	0.03	0.36	0.72	
Block type	-0.00	0.01	-0.04	0.96	
Cue	0.19	0.01	14.16	<0.001	***
PPS * previous choice	-0.06	0.01	-5.23	<0.001	***
Block type * previous choice	-0.02	0.01	-1.42	0.10	
PPS * block type	-0.00	0.01	-0.14	0.89	
PPS * cue	-0.04	0.01	-3.68	<0.001	***
Block type * cue	0.03	0.01	2.67	0.015	*
Previous choice * PPS * block type	0.00	0.01	0.47	0.63	
Cue * PPS * block type	0.01	0.01	0.87	0.38	

Table S3.1: Results of the logistic model, *Experiment 1.* Corrected R^2 = 0.404, Number of observations = 42,601, *SE*: standard error of estimate. PPS: psychosis proneness score

Variable	β	SE	z	p	sig.
Intercept	0.05	0.07	0.72	0.47	
Stimulus	0.81	0.01	53.60	<0.001	***
Discriminability	-0.04	0.01	-2.89	0.003	**
Previous stimulus	-0.04	0.02	-2.81	0.004	**
Previous choice	0.08	0.01	5.23	<0.001	***
PPS	0.01	0.07	0.10	0.92	
Block type	0.01	0.02	0.44	0.66	
Cue	0.47	0.01	32.56	<0.001	***
PPS * previous choice	-0.07	0.01	-5.24	<0.001	***
Block type * previous choice	-0.04	0.01	-2.80	0.005	**
PPS * block type	0.02	0.01	1.33	0.17	
PPS * cue	0.09	0.01	7.15	<0.001	***
Block type * cue	-0.01	0.01	-0.73	0.50	
Previous choice * PPS * block type	0.03	0.01	2.22	0.03	*
Cue * PPS * block type	0.00	0.01	-0.04	0.97	

Table S3.2: Results of the logistic model, *Experiment 2.*

Note: corrected R^2 = 0.32, Number of observations = 31,160. Comparable results from model with an additional predictor for block sequence design (0=old design, 1=new design), not displayed (β=0.05 ± 0.06, z=0.82, p=0.41).

Variable	β	SE	*z*	*p*	sig.
Cue model (eq. S3.1)					
Intercept	-0.01	0.03	-0.40	0.69	
Stimulus	1.35	0.01	97.26	<0.001	***
Cue	0.19	0.01	14.13	<0.001	***
Block and choice history (eq. S3.2)					
Intercept	-0.01	0.03	-0.36	0.72	
Stimulus	1.43	0.01	108.99	<0.001	***
Previous stimulus	-0.06	0.01	-3.70	<0.001	***
Block type	-0.00	0.01	-0.27	0.78	
Previous choice	0.09	0.01	5.94	<0.001	***
Previous choice * block type	-0.01	0.01	-1.35	0.176	
Choice history and previous discriminability (eq. S3.3)					
Intercept	0.00	0.03	0.03	0.98	
Stimulus	1.42	0.13	111.93	<0.001	***
Previous stimulus	-0.04	0.01	-2.66	0.007	**
Previous choice	-0.002	0.02	-0.18	0.86	
Previous discriminability	-0.01	0.01	-1.02	0.31	
Previous choice * previous discriminability	0.05	0.01	6.46	<0.001	***

Table S3.3: Test models, *Experiment 1.*

Variable	β	SE	z	p	sig.
Cue model (eq. S3.1)					
Intercept	0.05	0.07	0.64	0.52	
Stimulus	0.79	9.01	55.57	<0.001	***
Cue	0.46	0.01	32.18	<0.001	***
Block and choice history (eq. S3.2)					
Intercept	0.04	0.07	0.68	0.50	
Stimulus	0.99	0.01	71.94	<0.001	***
Previous stimulus	-0.05	0.01	-3.58	<0.001	***
Block type	0.01	0.01	1.03	0.30	
Previous choice	0.11	0.01	7.64	<0.001	***
Previous choice * block type	-0.03	0.01	-2.48	0.01	*
Choice history and previous discriminability (eq. S3.3)					
Intercept	0.02	0.08	0.31	0.75	
Stimulus	1.00	0.01	73.34	<0.001	***
Previous stimulus	-0.03	0.01	-1.84	0.06	.
Previous choice	-0.21	0.05	-3.94	<0.001	***
Previous discriminability	-0.02	0.07	-0.39	0.69	
Previous choice * previous discriminability	-0.48	0.07	-6.21	<0.001	***

Table S3.4: Test models, *Experiment 2.*

Variable	β	SE	*z*	*p*	sig.
Intercept	0.02	0.03	0.47	0.63	
Stimulus	1.35	0.01	93.93	<0.001	***
Discriminability	-0.08	0.01	-6.17	<0.001	***
Previous stimulus	-0.04	0.02	-3.03	0.002	**
Cue	0.16	0.02	8.71	<0.001	***
PPS	0.04	0.03	1.10	0.27	
Block type	-0.00	0.02	-0.03	0.97	
Previous choice	0.09	0.02	5.96	<0.001	***
Previous motor response	**0.06**	**0.02**	**2.44**	**0.01**	*
PPS * cue	-0.06	0.02	-3.27	0.001	**
Block type * cue	0.06	0.02	2.45	0.01	*
PPS * block type	-0.00	0.03	-0.13	0.89	
PPS * previous choice	-0.06	0.01	-5.17	<0.001	***
Previous choice * block type	-0.02	0.01	-1.39	0.16	
PPS * previous motor response	**0.05**	**0.03**	**2.21**	**0.03**	*
Cue * PPS * block type	0.02	0.02	0.90	0.37	
Previous choice * PPS * block type	0.00	0.01	0.48	0.63	

Table S3.5: Results of the logistic model, controlling for previous motor response – *Experiment 1.*

Variable	β	SE	*z*	*p*	sig.
Intercept	0.04	0.07	0.61	0.54	
Stimulus	0.81	0.02	53.59	<0.001	***
Discriminability	-0.04	0.01	-2.90	0.003	**
Previous stimulus	-0.04	0.02	24.24	0.004	**
Cue	0.48	0.02	24.24	<0.001	***
PPS	-0.02	0.07	-0.25	0.80	
Block type	0.02	0.03	0.43	0.66	
Previous response	0.08	0.015	5.53	<0.001	***
Previous motor response	**-0.004**	**0.00**	**-1.42**	**0.15**	
PPS * cue	0.096	0.02	5.00	<0.001	***
Block type * cue	-0.02	0.03	-0.72	0.47	
PPS * block type	0.05	0.04	1.35	0.17	
PPS * previous choice	-0.07	0.01	-5.23	<0.001	***
Previous choice * block type	-0.04	0.01	-2.80	0.005	**
PPS * previous motor response	**-0.00**	**0.00**	**-0.84**	**0.40**	
Cue * PPS * block type	0.00	0.02	0.05	0.96	
Previous choice * PPS * block type	0.03	0.01	2.12	0.03	*

Table S3.6: Results of the logistic model, controlling for previous motor response – *Experiment 2.*

Variable	β	SE	*z*	*p*	sig.
Intercept	-0.07	0.03	-2.24	0.03	*
Stimulus	1.34	0.01	94.84	<0.001	***
Discriminability	0.04	0.01	-6.17	<0.001	***
Previous choice	0.06	0.01	5.12	<0.001	***
PPS	0.01	0.03	0.35	0.72	
Block type	-0.00	0.01	-0.06	0.95	
Cue	0.19	0.01	14.23	<0.001	***
PPS * previous choice	-0.06	0.01	-5.17	<0.001	***
Block type * previous choice	-0.02	0.01	-1.61	0.10	
PPS * block type	-0.00	0.01	-0.13	0.89	
PPS * cue	-0.04	0.01	-3.69	<0.001	***
Cue * block type	0.03	0.01	2.90	0.003	**
Previous choice * PPS * block type	0.00	0.01	0.45	0.65	
Cue * PPS * block type	0.01	0.01	0.89	0.37	

Table S3.7: Results of the logistic model, without stimulus history – *Experiment 1.*

Variable	β	SE	*z*	*p*	sig.
Intercept	0.00	0.00	0.71	0.47	
Stimulus	0.80	0.01	54.61	<0.001	***
Discriminability	-0.03	0.01	-2.90	0.003	**
Previous choice	0.06	0.01	4.78	<0.001	***
PPS	0.00	0.01	0.10	0.92	
Block type	0.00	0.01	0.41	0.67	
Cue	0.04	0.01	32.58	<0.001	***
PPS * previous choice	-0.07	0.01	-5.26	<0.001	***
Block type * previous choice	-0.04	0.01	-2.95	0.003	**
PPS * block type	-0.02	0.01	1.37	0.17	
PPS * cue	0.08	0.01	-7.14	<0.001	***
Cue * block type	-0.01	0.01	-0.43	0.66	
Previous choice * PPS * block type	0.03	0.01	2.22	0.02	*
Cue * PPS * block type	0.00	0.01	0.00	0.99	

Table S3.8: Results of the logistic model, without stimulus history – *Experiment 1.*

2. Random slopes

Below, we describe the mathematical reasoning behind our choice of random slopes in the main logistic model. In short, we do not incorporate random slopes in the analysis of neither *Experiment 1* nor *Experiment 2* due to convergence issues, which can falsify regression results. In the following models, *r* refers to choice, or response, *c* refers to the cue, *s* refers to the stimulus, and d_t is the discriminability of a given trial's stimulus.

Experiment 1. A full model with a random slope for cue, previous choice and previous stimulus, i.e.

$$r_t \sim (1|sbj) + (1|block{:}sbj) + (1+r_{t-1}|sbj) + (1+c_t|sbj\_id) + (1+s_{t-1}|sbj) + d_t + s_t + s_{t-1} + c_t * PPS * blocktype + r_{t-1} * PPS * blocktype \tag{S3.4}$$

was nearly unidentifiable, which can compromise model results. A model with a random slope for previous choice, i.e.

$$r_t \sim (1|sbj) + (1|block{:}sbj) + (1+r_{t-1}|sbj) + t_t + s_t + s_{t-1} + c_t * PPS * blocktype + r_{t-1} * PPS * blocktype \tag{S3.5}$$

did not converge.

When implementing a model with a random slope for cue, i.e.

$$r_t \sim (1|sbj\_id) + (1|block{:}sbj\_id) + (1+c_t|sbj\_id) + s_t + d_t + s_{t-1} + c_t * PPS * block\ type + r_{t-1} * PPS * block\ type \tag{S3.6}$$

the model was near-unidentifiable and statistical conclusions based on this model fit may be inappropriate. Finally, a model with a random slope for previous stimulus,

$$r_t \sim (1|sbj) + (1|block{:}sbj) + (1+s_{t-1}|sbj) + s_t + d_t + s_{t-1} + c_t * PPS * blocktype + r_{t-1} * PPS * blocktype$$

failed to converge as well. In conclusion, data of *Experiment 1* did not support random slopes in the logistic model.

Experiment 2. A full model with random slopes for cue, choice- and stimulus history, i.e.

$$r_t \sim (1|sbj) + (1|block{:}sbj) + (1+r_{t-1}|sbj) + (1+c_t|sbj\_id) + (1+s_{t-1}|sbj) + t_t + s_t + s_{t-1} + c_t * PPS * blocktype + r_{t-1} * PPS * blocktype \tag{S3.7}$$

converged, but there were problems with avoiding singular fits. This means that the data does not support the full structure of complex random effects. A model with a random slopes only for cue effects,

$$r_t \sim (1|sbj\_id) + (1|block{:}sbj\_id) + (1+c_t|sbj\_id) + s_t + d_t + s_{t-1} + c_t * PPS * block\ type + r_{t-1} * PPS * block\ type \tag{S3.8}$$

failed to converge, as did a model with only a random slope for choice history,

$$r_t \sim (1|sbj) + (1|block{:}sbj) + (1+r_{t-1}|sbj) + t_t + s_t + s_{t-1} + c_t * PPS * blocktype + r_{t-1} * PPS * blocktype \tag{S3.9}$$

A model with a random slope for stimulus history,

$$r_t \sim (1|sbj) + (1|block{:}sbj) + (1+s_{t-1}|sbj) + s_t + d_t + s_{t-1} + c_t * PPS * blocktype + r_{t-1} * PPS * blocktype \tag{S3.10}$$

did not converge either, so that no random slopes were incorporated in the analysis of *Experiment 2* data.

S4. Separate effects of delusional vs. hallucinatory tendency

Across both experiments, participants responded to two measures of psychosis proneness, the PDI and the CAPS.[11,12] While the PDI measures an individual's proneness to delusional ideation, the CAPS assesses the tendency for hallucinatory experiences. In the main analysis, we summed over these two z-transformed measures to arrive at a more general measure of psychosis proneness. To investigate the validity of this approach and to test some specific hypotheses regarding these two measures, we here investigate the measures in isolation. We compute a logistic regression with equivalent predictors as in the main model, with the only difference of using z-transformed PDI- and CAPS-values instead of our compound psychosis proneness score (PPS) that are used in the main analysis. Results are summarized in tables **S4.1-4.**

Experiment 1. In the auditory task, choice history interacted significantly with z-transformed PDI (β=-0.006, SE=0.001, $p<0.001$) and CAPS scores (β=-0.05, SE=0.01, $p<0.001$). Cue reliance also significantly interacted with both measures (PDI: β=-0.004, SE=0.001, $p<0.05$, CAPS: β=-0.06, SE=0.02, $p<0.05$).

Experiment 2: The interaction between choice history and individual score was significant for both PDI (β=-0.09, SE=0.01, $p<0.001$) and CAPS (β=-0.04, SE=0.01, $p<0.001$) scores. Interestingly, cue reliance interacted significantly only with PDI score (β=0.17, SE=0.02, $p<0.001$), but not with CAPS score (β=0.01, SE=0.02, $p=0.42$).

Across experimental modalities and measures of psychosis proneness, a significant interaction between psychosis proneness score and choice history effects can be observed. This suggests that reduced reliance on choice history is a general feature of information processing in psychosis proneness, regardless of the specific experiential quality. This finding provides empirical support for predictive coding accounts of psychosis.

The interaction between PDI- and CAPS scores and cue reliance was inconsistent across experiments. Our data hence does not support a modulation of each measure of our measures of psychosis proneness and cue.

Variable	β	SE	*z*	*p*	*sig*
(Intercept)	-0.001	0.03	-0.36	0.72	
Stimulus	1.35	0.01	93.84	<0.001	***
discriminability	-0.07	0.01	-6.12	<0.001	***
cue	0.16	0.02	8.75	<0.001	***
PDI	0.01	0.03	0.21	0.84	
block type	0.00	0.03	-0.003	0.99	
previous stimulus	-0.05	0.02	-3.03	0.002	**
previous choice	0.09	0.02	5.91	<0.001	***
cue * PDI	-0.05	0.02	-2.69	0.007	**
cue * block type	0.06	0.03	2.43	0.01	*
PDI * block type	0.00	0.03	-0.14	0.88	
PDI * previous choice	-0.07	0.01	-5.32	<0.001	***
previous choice * block type	-0.01	0.01	-1.42	0.15	
cue * previous choice	0.01	0.01	0.80	0.42	
cue * PDI * block type	0.04	0.02	1.44	0.15	
PDI * previous choice * block type	0.01	0.01	0.42	0.67	
cue * PDI * previous choice	-0.02	0.01	-1.57	0.11	

Table S4.1 Logistic choice model with PDI scores only, *Experiment 1.*

Variable	β	SE	*z*	*p*	*sig*
(Intercept)	-0.01	0.003	-0.36	0.71	
Stimulus	1.34	0.01	93.85	<0.001	***
discriminability	-0.07	0.01	-6.14	<0.001	***
cue	0.16	0.02	8.75	<0.001	***
CAPS	0.02	0.03	0.54	0.58	
block type	0.00	0.03	-0.01	0.99	
previous stimulus	-0.05	0.01	-2.98	0.003	**
previous choice	0.09	0.02	5.86	<0.001	***
cue * CAPS	-0.06	0.02	-3.28	0.001	**
cue * block type	0.06	0.02	2.43	0.01	*
CAPS * block type	0.00	0.03	-0.23	0.82	
CAPS * previous choice	-0.05	0.01	-4.27	<0.001	***
previous choice * block type	-0.02	0.01	-1.40	0.16	
cue * previous choice	0.01	0.01	0.81	0.41	
cue * CAPS * block type	0.00	0.02	0.14	0.89	
CAPS * previous choice * block type	0.00	0.01	0.42	0.67	
cue * CAPS * previous choice	-0.02	0.01	-1.43	0.15	

Table S4.2 Logistic choice model with CAPS scores only, *Experiment 1.*

Variable	β	SE	*z*	*p*	*sig*
(Intercept)	0.04	0.07	0.61	0.54	
Stimulus	0.81	0.01	53.25	< 0.001	***
coherence	-0.04	0.01	-2.9	0.004	**
cue	0.47	0.02	24.17	<0.001	***
PDI	0.006	0.07	0.09	0.93	
block type	0.02	0.04	0.43	0.67	
previous stimulus	-0.04	0.01	-2.76	0.006	**
previous choice	0.08	0.01	5.34	< 0.001	***
cue * PDI	0.17	0.02	8.62	< 0.001	***
cue * block type	-0.01	0.03	-0.50	0.61	
PDI * block type	0.05	0.04	1.24	0.21	
PDI * previous choice	-0.09	0.01	-6.55	< 0.001	***
previous choice * block type	-0.03	0.01	-2.68	0.007	**
cue * previous choice	-0.02	0.01	-1.48	0.14	
cue * PDI * block type	-0.01	0.03	-0.32	0.75	
PDI * previous choice * block type	0.03	0.01	1.98	0.05	*
cue * PDI * previous choice	0.00	0.01	0.33	0.74	

Table S4.3 Logistic choice model with PDI scores only, *Experiment 2.*

Variable	β	SE	*z*	*p*	*sig*
(Intercept)	0.04	0.07	0.56	0.57	
Stimulus	0.80	0.01	53.16	<0.001	***
coherence	-0.04	0.01	-2.93	0.003	**
cue	0.47	0.02	23.99	<0.001	***
CAPS	-0.04	0.07	-0.54	0.59	
block type	0.01	0.04	0.37	0.71	
previous stimulus	-0.04	0.02	-2.79	0.005	**
previous choice	0.08	0.01	5.71	<0.001	***
cue * CAPS	0.01	0.02	0.81	0.42	
cue * block type	-0.01	0.03	-0.54	0.59	
CAPS * block type	0.05	0.04	1.33	0.18	
CAPS * previous choice	-0.04	0.01	-3.33	<0.001	***
previous choice * block_type	-0.04	0.01	-2.71	0.006	**
cue * previous choice	-0.02	0.01	-1.29	0.19	
cue * CAPS * block type	0.02	0.03	0.61	0.54	
CAPS* previous choice * block type	0.03	0.01	2.04	0.04	*
cue * CAPS * previous choice	0.00	0.01	-0.18	0.85	

Table S4.4 Logistic Choice model with CAPS scores only, *Experiment 2.*

S5. Effects of choice confidence

Previous research demonstrates that choice history biases and serial dependencies are modulated by decision uncertainty and confidence.[9,10,13–15] Specifically, choice history biases appear to be confidence-weighted, with highly confident past choices exerting a larger bias on the current perceptual choice. Following a Bayesian account of perception, it is beneficial to integrate past information with current sensory input especially when past information is highly reliable and/ or current sensory information is uncertain.[16]

In Bayesian terms, a belief is expressed as a probability distribution with a mean and a variance. While the mean signifies the current estimate of the belief or sensory input, the reliability or certainty of a signal is quantified by its precision, or inverse variance.[17] Precision is a core concept of predictive coding models of psychosis[17–19] and is thought to balance different sources of information across the cortical hierarchy. In inference, entertaining accurate beliefs about the precision of a signal is therefore very important, and if precision is misrepresented, false inferences may be the consequence.[20] In psychosis, it has been suggested that imprecise priors at lower, sensory levels may be compensated by overly precise conceptual priors at higher levels of the cortical hierarchy.[19,21,22]

We here investigated whether previous trial discriminability, as a rough approximation for the precision of incoming sensory information, modulates choice history biases. Previous research suggests that choice history biases are more pronounced when sensory uncertainty is higher, i.e. during more difficult trials.[3] It follows that in psychosis, imprecise sensory-level priors which we here operationalize through choice history biases, should play out especially during more difficult trials where sensory uncertainty is higher.

For this reason, we incorporated in the main logistic model a predictor for previous trial discriminability and its interaction with choice history. The model equation is given by

$$r_t \sim (1|sbj) + (1|block{:}sbj) + s_t + d_t + s_{t-1} + \mathbf{r_{t-1} * d_{t-1}} + c_t * PPS * blocktype + r_{t-1} * PPS * blocktype \qquad (S5.1)$$

Results are summarized in *Tables* **S5.1** and **S5.2**. Across both experiments, there was no main effect of previous trial discriminability (or coherence, respectively). However, across both datasets, the effect of previous choice was significantly modulated by previous trial discriminability (*Experiment 1:* β=-0.04, SE=0.01, p<0.001; *Experiment 2:* β=-0.47, SE=0.07, p<0.001). Previous discriminability hence modulates the bias exerted by choice history across both experiments, with more difficult stimuli in the previous trial exerting a smaller bias on the current choice. This is in line with previous findings.[13,23]

In *Experiment 2,* there were significant main effects of stimulus and coherence as well as cue. As in *Experiment 1,* choice history bias significantly interacted with previous trial's coherence, which indicates a stronger choice history bias resulting from harder trials (lower coherence, note the change in sign). In *Experiment 2,* choice history biases are significantly modulated by psychosis proneness, with decreasing reliance on choice history in more psychosis prone individuals also in the easy subset of trials. As in the main model, there was an additional increased reliance on cue information in psychosis proneness, as indicated by a positive significant β for the interaction *cue * PPS.*

Variable	β	SE	*z*	*p*	sig
Intercept	0.00	0.04	-0.13	0.89	
stimulus	1.34	0.01	93.36	<0.001	***
discriminability	-0.07	0.01	-6.10	<0.001	***
previous stimulus	-0.02	0.02	-1.38	0.17	
previous choice	0.01	0.02	0.49	0.62	
previous discriminability	0.00	0.01	-0.50	0.61	
cue	0.16	0.02	8.79	<0.001	***
PPS	0.01	0.03	0.38	0.70	
block type	0.00	0.01	-0.06	0.95	
previous choice * previous discriminability	**0.04**	**0.01**	**6.31**	**<0.001**	***
cue * PPS	-0.06	0.02	-3.23	0.001	**
cue * block type	0.07	0.02	2.67	0.007	**
PPS * block type	0.00	0.03	-0.13	0.89	
PPS * previous choice	-0.06	0.01	-5.21	<0.001	***
previous choice * block type	-0.02	0.01	-1.65	0.09	
cue * PPS * block type	0.02	0.02	0.86	0.39	
previous choice * PPS * block type	0.00	0.01	0.44	0.66	

Table S5.1 Logistic choice model, extended by previous trial discriminability, *Experiment 1.*

Variable	β	SE	z	p	sig
Intercept	-0.01	0.08	-0.14	0.89	
stimulus	0.81	0.02	53.62	<0.001	***
discriminability	-0.04	0.01	-2.87	0.004	**
previous stimulus	-0.02	0.02	-1.03	0.30	
previous choice	-0.23	0.06	-4.19	<0.001	***
previous discriminability	-0.08	0.07	-1.06	0.29	
cue	0.48	0.02	24.23	<0.001	***
PPS	-0.02	0.07	-0.27	0.79	
block type	0.02	0.04	0.44	0.66	
previous choice * previous discriminability	-0.47	0.07	-5.90	<0.001	***
cue * PPS	0.09	0.01	5.09	<0.001	***
cue * block type	-0.02	0.02	-0.67	0.50	
PPS * block type	0.05	0.04	1.33	0.18	
PPS * previous choice	-0.07	0.01	-5.27	<0.001	***
previous choice * block type	-0.04	0.01	-2.80	0.005	**
cue * PPS * block type	0.00	0.03	-0.03	0.97	
previous choice * PPS * block type	0.03	0.01	2.21	0.03	*

Table S5.2 Logistic choice model, extended by previous trial discriminability, *Experiment 2.*

S6. Cue effects

By design, cue- and stimulus identity co-occurred in 75% of cases. Hence, whenever performance is above chance level, behaviour will seem cue-congruent. To assess whether participants relied on the cue in the expected way independent of the individual task performance, we computed a cue congruency index, or CCI per subject, which was given by (see [24]):

$$CCI = CR_{CC} - CR_{CI} \tag{S6.1}$$

The CCI is given by the percentage of correct responses in cue-congruent trials, CR_{CC}, minus the percentage of correct responses in cue-incongruent trials, CR_{CI}. Here, a value of 0 would indicate that the cue had no effect on behaviour, whereas a value of 100 would indicate perfect reliance on the cue. Results are shown in figures **S6.1** and **S6.2.** Mean CCI in *Experiment 1* was 32.16 (range 17.85-62.98). Similarly, in *Experiment 2,* mean CCI was 39.06 (range 2.93-69.12). This result suggests that participants relied on cue information across experiments, independent of their task performance, and completed the task as expected.

There were no significant temporal dynamics over the course of the experimental blocks related to the average CCI, as illustrated in figures **S6.3** and **S6.4.**

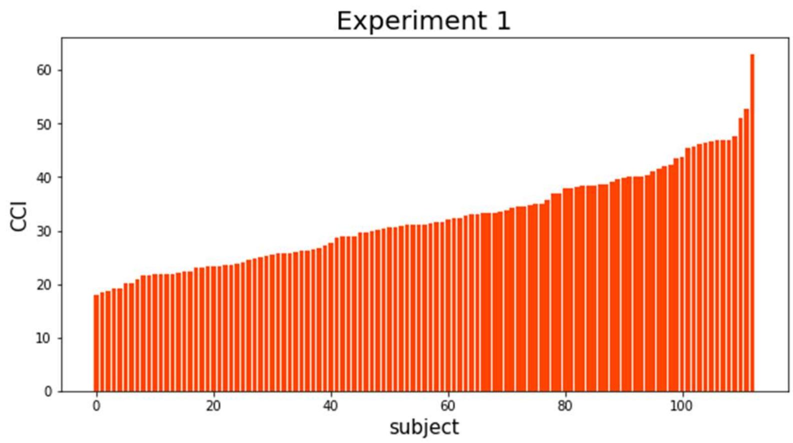

Figure S6.1: CCI scores per subject in *Experiment 1.*

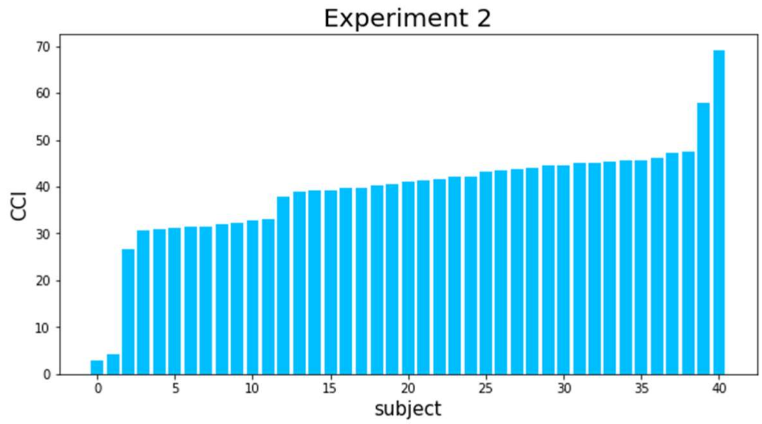

Figure S6.2: CCI scores per subject in *Experiment 2.*

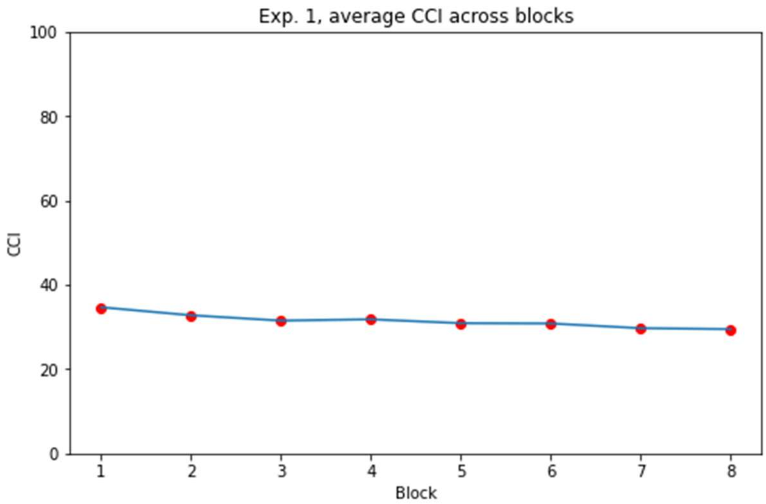

Figure S6.3 Block-wise average CCIs in *Experiment 1* show no temporal dynamics, e.g. related to learning effects.

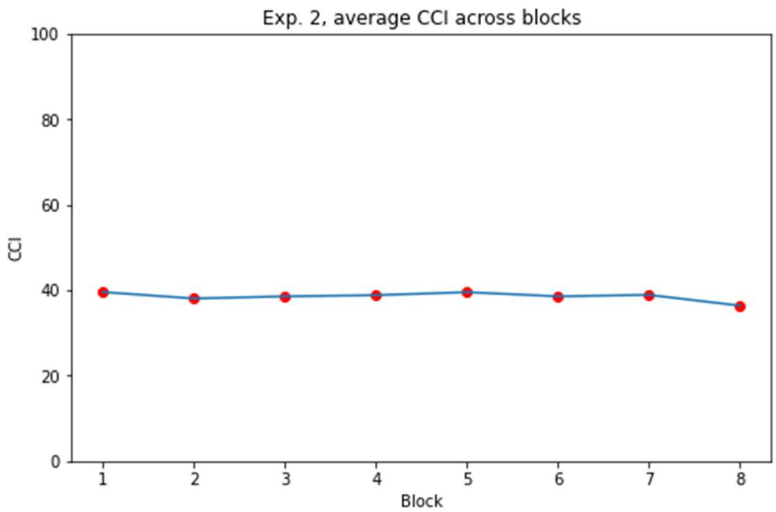

Figure S6.4 Block-wise average CCIs in *Experiment 2* show no temporal dynamics.

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