**Introduction**

As we navigate the world around us, the statistics of the environment can change dramatically. The efficient coding hypothesis postulates that neurons match their limited dynamic range to the statistics of incoming sensory signals1. Thus, through adaptation of their response properties, neurons can preserve their ability to encode information within many types of environments2–4. Neuronal adaptation to the statistics of the environment has been found throughout different sensory modalities and brain regions5–13. In the auditory system, neurons exhibit contrast gain control, adapting the gain of their response function to match the variability in level (contrast) of the incoming sounds14–18. Yet it remains unknown whether and how the dynamics of contrast gain control in the auditory system inform behavior, as a direct link between neuronal adaptation and behavior has not been previously established. The goal of our study was to test the hypothesis that efficient coding in auditory cortex shapes behavioral performance in an auditory task.

The efficient coding hypothesis has been formally implemented through normative models of brain function3,4,19–22. These models allow us to assess whether and how neuronal adaptation shapes sensory information and simulate how neural function constrains behavior. There has been previous work demonstrating that efficient codes can explain psychophysical biases23 and shape the rate of information transmission when stimulus statistics change dynamically20,22. These studies, which are either theoretical in nature or based in human psychophysics, rely on assumptions of neuronal mechanisms of efficient coding that were not simultaneously measured. As such, there are no studies combining behavioral psychophysics with recordings of brain activity to simultaneously test the neural assumptions and behavioral predictions of these models.

Psychophysical studies suggest that the auditory system exhibits adaptation to acoustic contrast. In humans, target volume discriminability is greater in low contrast than in high contrast, an effect consistent with gain control observed in primary auditory cortex24. Similar effects have also been shown in ferrets performing an acoustic localization task, where it was demonstrated that neural responses in the inferior colliculus of anesthetized ferrets changed in a manner consistent with previously observed perceptual shifts10. However, it remains unclear whether the observed behavioral effects are indeed due to changes in gain in auditory neurons, as previous behavioral studies were not performed with simultaneous neural recordings, so a direct relationship between neural gain and perceptual performance has yet to be assessed.

Our first goal for the study was to build a formal framework based on efficient coding to model the dynamics of contrast gain control, allowing us to predict how behavioral performance adapts after a change in contrast. We then derived a novel generalized linear model (GLM) to estimate moment-to-moment changes in neural gain, and found that gain in auditory cortex adapted similarly to the efficient coding model predictions. Next, to directly test the role of efficient coding in auditory behavior, we trained mice to detect targets in different contrast backgrounds. Contrast-induced changes in behavioral sensitivity and detection dynamics followed the model predictions. Furthermore, we found that auditory cortex was necessary for target detection in the presence of noise. Building on this finding, we found that population activity in auditory cortex was predictive of individual differences in behavior and that the dynamics of cortical encoding of targets had time courses similar to our model and the observed behavior. Finally, we used linear nonlinear models to monitor cortical gain during the task, finding that variability in neural gain predicted variability in task performance. Combined, our results identify a novel relationship between efficient neuronal coding and acoustic behavior, and provide a normative framework that can be used to predict the dynamics of behavioral performance in response to changing sensory environments.

**Results**

*A novel target-in-noise detection task and normative model for task predictions.*

To assess how perceptual performance is impacted by stimulus contrast, we devised a GO/NO-GO task in which mice were trained to detect targets embedded in different contrast backgrounds. During each trial, the mouse was presented with dynamic random chords (DRCs) of one contrast, which transitioned after 3 s to the other contrast. At variable delays after the contrast transition, broad-band target chords were superimposed on the background chords, and mice were trained to lick for a water reward upon hearing the target. Target trials were interleaved with noise-only trials, during which the mouse was trained to withhold licking, but would receive a 7s timeout for licking after the contrast switch (Figure 1a,b). To assess behavioral sensitivity to targets, we parametrically varied target volume in each contrast (Figure 1c, top panel) and to assess behavioral adaptation, we parametrically varied target timing (Figure 1c, bottom panel). This stimulus design allowed us to quantitatively test whether and how the dynamics of adaptation to background contrast affect behavioral performance.

To predict the optimal time course of contrast gain control and its impact on target detection behavior, we developed a normative model of task performance constrained by efficient neural coding. In this model, we simulated a neuron designed to estimate the contrast of the recent stimulus by adjusting the gain of its nonlinearity (Figure 1d, panels 1-3; *Online Methods*)20,22. Adding targets at different levels and times relative to contrast transitions then allowed us to probe the sensitivity of the model neuron to targets of varying strength over the time course of adaption (Supplementary Figure 1c,d). When varying target strength and measuring target discriminability, we found decreased “detection” thresholds and steeper slopes in low contrast relative to high contrast (Figure 1e). When varying target timing, we observed two timescales which affected the target discriminability: 1) An abrupt drop in discriminability after a transition to high contrast; 2) A slower change in discriminability in both contrasts, as the gain of the model neuron adapted to the background (Figure 1f,g). We quantified these asymmetric dynamics by fitting exponential functions to each transition. To summarize, the normative model poses three primary predictions: When adapted to low contrast, 1) target detection thresholds will be lower, and 2) sensitivity to changes in target volume will be higher; 3) Discriminability over time will be asymmetric: rapidly decreasing after a switch to high contrast, but slowly increasing after a switch to low contrast (Figure 1h).

*Estimated cortical gain dynamics follow normative model predictions.*

Most previous work on contrast gain control utilized static models of contrast adaptation, measuring the steady-state gain after the neuron has fully adapted to the new stimulus15,17,24,25, but see26,27. A major goal of the current study was to analyze the dynamics of gain control, so we developed a Poisson GLM to estimate the gain of neurons in auditory cortex at each time step following a contrast transition. This model was fit to data recorded from the auditory cortex of an untrained mouse (n = 97 neurons) presented with 3s alternations of low and high contrast noise (Figure 2a,b). A brief description of the model follows (see *Online Methods* for more detail).

The inference model is a Poisson GLM which decomposes the relationship between spiking activity () and the presented sounds () into a stimulus component (), contrast component (), and an interaction between the stimulus and the contrast (). We then calculated a gain modulation index () from the fitted model parameters (Figure 2b). For comparison, we also fit previously described linear-nonlinear models to each neuron15,17,24,25, one with a static output nonlinearity (static-LN), and one with a contrast-dependent output nonlinearity (GC-LN, Figure 2c). Model results for a representative neuron are plotted in Figure 2d-g. Qualitatively, the GLM with gain control (GC-GLM), outperforms standard LN models, principally by capturing the adaptation after the transition (Figure 2d, middle panel) and allowed us to analyze gain modulation over time, (Figure 2d, bottom panel; Figure 2g). Importantly, the fit of the GC-LN model and GC-GLM model both demonstrate gain control, characterized by high gain in low contrast and low gain in high contrast (Figure 2f and g, respectively), suggesting that both models capture similar gain estimates.

To test whether the GC-GLM could better account for the data, we compared cross-validated correlations of the model predictions with the trial averaged PSTH for all each neuron, finding a significant effect of model type on the correlations (n = 97 neurons; Kruskall-Wallis test: *H*(2) = 93.61, p = 6.70e-21). Post-hoc Wilcoxon Sign-Rank tests found that the GC-GLM correlation was significantly higher (Median (*Mdn*) = 0.75, Inter-Quartile Range (*IQR*) = 0.24) compared to the GC-LN model (*Mdn* = 0.54, *IQR* = 0.49, *p* = 4.41e-6) and the static-LN model (*Mdn* = 0.25, *IQR* = 0.73, *p* = 9.56e-10). Consistent with previous studies, we also found that the LN model with gain control outperformed the static model (*p* = 3.50e-6, Figure 2g). We then quantified whether the GLM detected significant gain control in the population by subtracting the gain estimate in low contrast from high contrast after the value of stabilized (1s post transition) and found significant gain control (*Mdn*: -0.10, *IQR*: 0.35, Wilcoxon sign-rank test: *rank* = 233, *Z* = -2.90, *p* = 0.004; Figure 2i). To further validate the GLM estimates of gain, we compared the gain control index from the GC-GLM to those of the GC-LN model, and found a significant relationship between the two measures (linear regression: *F*(1,95) = 12.20, *p* = 7.33e-4, *R2* = 0.11; Figure 2j). These results demonstrate that the GC-GLM better accounts for the neural data by incorporating gain adaptation dynamics and conclude that this method captures a similar estimate of neural gain when compared to standard models.

Using the GC-GLM, we estimated the time course of gain control by computing conditioned on the contrast transition and fit each trace with an exponential function (Figure 2g). In neurons with gain control, the average time course of demonstrates asymmetric adaptation, rapidly decreasing after a switch to high contrast, and slowly increasing after a switch to low contrast (n = 45 neurons; Figure 2k). Within this same population, we quantified adaptation to each contrast using the time constant () of each exponential fit, finding significantly longer time constants in low contrast (*Mdn* = 0.29, *IQR* = .39) relative to high contrast (*Mdn* = 0.048, *IQR* = 0.094; Wilcoxon sign-rank test: *rank* = 918, *Z*  = 4.52, *p* = 6.16e-6). This asymmetry in gain adaptation agreed with the predictions of the normative model (Figure 1g) and with previously described behavior of optimal variance estimators19. Next, we tested whether similar dynamics were reflected in behavioral sensitivity to targets in noise.

*Mouse behavioral detection is modulated by background contrast.*

Mice were initially trained in a simple version of the GO/NO-GO task, where they were required to lick in response to a target, and withhold licking on trials without a target (Figure 1b, 3a). Mice learned this task reliably, typically reaching criterion performance of 80% correct within 2-3 weeks in either contrast (Figure 3b). Observed false alarm rates were significantly larger in high contrast compared to low contrast (Supplementary Figure 3a), suggesting that detection is more difficult in high contrast, which we discuss next.

By varying the volume of presented targets, we collected psychometric curves for each mouse in each contrast. Figure 3c plots the performance of an example mouse overlaid with average psychometric fits, whereas Figure 3d plots the group averages for each contrast. Across all mice (n = 25), we found that targets were easier to detect in low contrast, observing significantly lower detection thresholds in low contrast (Mean (*M*)= 7.47, standard deviation (*SD*) *=* 1.59) compared to high contrast (*M =* 13.20, *SD =* 2.54; paired t-test: *t(23)* = -8.71, *p* = 9.59e-9, Figure 3e). Next, we computed how sensitive mice were to changes in target volume by calculating the maximum slope of the psychometric curve for each mouse and found that in the full cohort of mice, there was no significant change in slope (Supplemental Figure 3b), which contradicted our normative model predictions (Figure 1e). Investigating further, we found that the range of target volumes had a significant effect on psychometric slopes. Namely, targets drawn from a narrow range resulted in steeper psychometric slopes than targets drawn from a wide range (Supplemental Figure 3c-f), regardless of the background contrast. To test the pure influence of contrast on psychometric slope, we tested a subset of mice with target volumes matched across the contrast conditions. In this cohort (n = 7; Figure 2f), we found significantly lower target thresholds in low contrast (*M* = 6.80, *SD =* 2.73) compared to high contrast (*M =* 14.96, *SD =* 3.51; paired t-test: *t(3)* = -3.59, *p* = 0.036; Figure 3g) and significantly steeper slopes in low contrast (*M* = 0.051, *SD =* 0.0068) compared to high contrast (*M =* 0.042, *SD =* 0.0064; paired t-test: *t(3)* = 3.42, *p* = 0.042; Figure 3h). These results demonstrate that background contrast has a substantial impact on detection threshold, and that mice are more sensitive to changes in the volume of targets presented in low contrast.

To assess behavioral adaptation to the background contrast, we presented targets at threshold volume at variable delays following the contrast transition. We observed behavioral time courses consistent with our normative model and with gain measured in auditory cortex: after a switch to high contrast, mice initially detected targets with high accuracy which decreased over time, while in low contrast we observed increasing detection rates over time (Figure 3i). We found that in high contrast, the first significant drop in performance occurred between the first two time points, while in low contrast the first significant increase in performance occurred between the first and third time points (Figure 3i, Table 1). Then, by fitting each mouse’s adaptation time course with an exponential function and comparing time constants for each contrast, we also found that behavioral adaptation is significantly faster in high contrast (*Mdn* = 0.023, *IQR* = 0.082) compared to low contrast (*Mdn =* 0.13, *IQR* = 0.13; Wilcoxon sign-rank test (n = 21): *rank*  = 547, *Z* = 2.75, *p* = 0.0060; Figure 3j). Taken together, these behavioral results confirm the three predictions from our model (Figure 1h): 1) Detection thresholds are lower in low contrast; 2) Psychometric slopes are higher in low contrast; 3) Performance decreases rapidly in high contrast, while increasing gradually in low contrast.

*Auditory cortex is necessary for detection in noise.*

Previous studies have shown that while gain control is present in many areas across the auditory pathway, it is strongest in auditory cortex15,24. As such, we hypothesized that auditory cortex was likely to be a key brain area supporting the detection of sounds in the presence of background noise, particularly when using background sounds known to modulate neuronal gain. To test whether auditory cortex is necessary for task performance, we inactivated auditory cortex using the GABA-A receptor agonist muscimol. In n = 2 untrained mice, we first validated that muscimol disrupts cortical coding of target sounds by applying muscimol topically to the cortical surface during passive playback of the behavioral stimuli, finding near complete suppression of target responses (Supplemental Figure 4a-f, *Supplemental Information*).

To test whether inactivation of auditory cortex affects behavioral performance, we repeated the same experiments in behaving mice, administering muscimol or saline bilaterally through chronically implanted cannulae (n = 4; Figure 4a). As observed in cortex, there was a profound decrease in the response rates to targets and noise in both contrasts (Figure 4b). We quantified these effects on the psychometric curve using a 3-way ANOVA with cortical intervention (muscimol or saline), contrast, and target volume as factors. We found significant main effects of cortical intervention (*F*(1,307) = 278.63, *p* = 3.83e-44), contrast (*F*(1,307) = 4.39, *p* = 0.037) and volume (*F*(6,307) = 40.90, *p =* 7.54e-36). Post-hoc tests showed that muscimol application significantly decreased hit rates by 31% (95% CI: [28,35]), whereas hit rates were significantly elevated in low contrast by 4.9% (95% CI: [2.6,7.6]). Furthermore, we observed significant interactions between target volume and cortical intervention (*F*(6,307) = 14.11, *p* = 4.47e-14), and between target volume and contrast (*F*(6,307) = 2.97, *p* = 7.87e-3), but no significant interaction between contrast and cortical intervention. To quantify the effects of muscimol on psychometric performance, we extracted the response rates to the loudest target, false alarm rates, thresholds, and slopes of psychometric functions fit to each session, and found that muscimol significantly reduced every measure of psychometric performance, with the exception of behavioral threshold (Figure 4c, Table 1). From these results, we can conclude that auditory cortex is necessary for performing target in noise detection, regardless of background contrast.

A potential alternative effect of muscimol is a general loss of function that is not specific to hearing target sounds. To control for this, we devised another task where mice (n = 2) detected targets in silence (Figure 4e), in addition to targets in noise (Figure 4d). To ensure equivalency between the two tasks, we took the highest-volume target trials in the noise task (25dB SNR in high contrast; Figure 4d, left panel), and removed the background noise during the target detection period (Figure 4e, left panel). As such, mice detected the exact same targets as in the previous task, but without the flanking noise, allowing us to test whether auditory cortex is specifically required for detection in the presence of noise.

To assess psychometric performance in this new task, we modulated detection difficulty by attenuating the volume of each target. As observed previously, inactivation of auditory cortex hindered detection in high contrast noise (Figure 4d, right panel). However, cortical inactivation had little effect on psychometric performance in silence (Figure 4e, right panel). We quantified these effects on the psychometric curve using a 3-way ANOVA with cortical intervention (muscimol or saline), task (detection in noise or silence), and target volume as factors. We found significant main effects of intervention (*F*(1,181) = 62.83, *p* = 3.62e-13), task (*F*(1,181) = 6.82, *p* = 9.86e-3), and volume (*F*(6,181) = 46.16, *p* = 1.69e-32). Post-hoc tests showed that muscimol significantly reduced hit rates by 21.8% (95% CI: [15.2,25.2]). Hit rates to targets presented in silence were significantly elevated by 6.7% relative to targets presented in noise (95% CI: [1.7,11.6]). Furthermore, we found significant interactions between cortical intervention and task type (*F*(1,181) = 6.36, *p* = 0.013), intervention and volume (*F*(6,181) = 3.47, *p* = 2.98e-3), and volume and task type (*F*(6,181) = 8.47, *p* = 5.43e-8). As before, we parameterized psychometric performance by fitting each session with a psychometric curve, and extracted the response rate at maximum target volume, false alarm rate, response rate at threshold volume, and psychometric slope. During the target in noise task, we found significant effects of muscimol on the response rates at maximum volume and threshold, a moderate effect on psychometric slope, and no effect on false alarm rate. However, muscimol application had no significant effect on any of these measures in the target in silence task (Figure 4f, Table 1). Taken together, these results show that while cortical inactivation and the presence or absence of background noise both affect behavioral performance, these effects interact: muscimol has a larger effect on performance when background noise is present.

Combined, our findings demonstrate that the auditory cortex is specifically required for detection in the presence of background noise. Our next goal was to test whether neuronal activity in AC is predictive of behavioral performance.

*Cortical codes predict individual behavioral performance.*

To better understand how representations in auditory cortex could give rise to behavior, we chronically recorded from populations of neurons in auditory cortex while mice performed the psychometric task (Figure 5a; n = 12 mice overall [n = 11 mice in low contrast sessions, n = 8 mice in high contrast sessions]).

To leverage our ability to simultaneously record from multiple neurons, we adapted a population vector approach28 to generate metrics of target from noise discriminability using population activity. This method allowed us to project trial distributions in -dimensional neural space along a single dimension which separated target and noise trials (Figure 5d, left panel; *Online Methods*). We then estimated the criterion projection value that best predicted whether each trial contained a target or noise29 (Figure 5d, right; *Online Methods*).

This population decoding method allowed us to estimate neurometric functions to directly compare to psychometric functions for each mouse (Figure 5e). On average, neurometric and psychometric functions were qualitatively similar (Figure 5f). To quantify the relationship between behavioral and neural performance, we calculated average thresholds and slopes for each mouse and used multiple linear regression to predict behavioral threshold from stimulus contrast and neuronal thresholds. This model significantly predicted the observed thresholds (*F*(1,16) = 16.20, *p* = 2.34e-5, *R2* = 0.74), revealing that neuronal thresholds (*β* = 0.50, *p* = 0.020) and contrast (*β* = 3.034, *p* = 0.043) were significant predictors (Figure 5g). We then tested whether neurometric and psychometric thresholds were similarly affected by background contrast using a two-way ANOVA, with thresholds as the dependent variable and threshold measure (psychometric or neurometric) and contrast as independent variables. We found a main effect of contrast (*F*(1) = 29.30, *p* = 5.00e-6), but no main effect of threshold measure (*F*(1) = 0.02, *p* = 0.89) or interaction between measure and contrast (*F*(1) = 0.04, *p* = 0.85), which demonstrates that behavioral and neural thresholds were similarly affected by background contrast. As expected, post-hoc t-tests found no difference between neural and behavioral thresholds (mean change [95% confidence interval] *=* 0.19 [-1.38, 1.76], *p* = 0.81), and that low contrast significantly decreased thresholds relative to high contrast (-4.77 [-6.34, -3.19], *p* = 5.43e-7). Taken together, these results demonstrate that population thresholds in auditory cortex are highly predictive of behavioral thresholds, and both behavior and neuronal thresholds are modulated by contrast as predicted by gain control.

Next, we applied the same statistical analysis to psychometric and neurometric slopes, finding that neurometric slopes and contrast significantly predicted behavioral slopes (multiple regression: *F*(1,16) = 12.00, *p* = 6.63e-4, *R2* = 0.60). Examination of the individual predictors found that neuronal slopes were significantly predictive (*β* = 0.67, *p* = 0.0018), while contrast was not predictive (*β* = 0.010, *p* = 0.16) of behavioral slopes (Figure 5h). Repeating the ANOVA described above we found a significant main effect of slope measure (*F*(1) = 5.88, *p* = 0.021) and contrast (*F*(1) = 8.31, *p* = 0.0068), but no interaction between the two (*F*(1) = 0.18, *p* = 0.67). Post-hoc testing revealed that neuronal slopes were significantly shallower than neuronal slopes (-0.015 [-0.027, -0.0024] PC/dB, *p* = 0.021). We also found that low contrast slopes were significantly shallower overall (-0.018 [-0.030, -0.0052] PC/dB, *p =* 0.0068), conflicting with our previous behavioral findings (Figure 3h). However, if we averaged only the sessions where mice were presented matched target volumes in low and high contrast, we found a significant main effect of contrast (*F*(1) = 5.98, *p* = 0.028) and slope measure (*F*(1) = 10.62, *p* = 0.0057). Post-hoc testing of this cohort revealed significantly steeper slopes in low contrast (0.0071 [0.00087, 0.013], *p =* 0.028), and significantly shallower slopes of the neurometric functions (-0.0094 [-0.016, -0.0032], *p* = 0.0057; Supplementary Figure 5a). These results were consistent with our previous behavioral findings (Figure 2h), demonstrating that when target volumes are matched, increases in stimulus contrast induce a decrease in neurometric and psychometric slopes.

Taken together, these results demonstrate that parameters of neurometric and psychometric functions are affected by contrast in similar ways, consistent with our normative model. We also find that individual variation in psychometric performance is predicted by population activity in auditory cortex, independently of the effect of contrast.

*Asymmetric neural adaptation to targets.*

Using the same population decoding approach described above, we measured how cortical discriminability of target from noise trials evolved as a function of time and contrast during sessions where mice heard targets at threshold volume at different offsets relative to the contrast switch. While neuronal adaptation was qualitatively similar to behavioral performance, we quantified adaptation using the procedure applied to the behavioral time courses (Figure 3i). As in behavior, we found that in high contrast the first significant drop in performance occurred between the first two target times, while the first significant drop in low contrast occurred between the first and third target times.Finally, to quantify the speed of neural adaptation, we fit the average neural discrimination time course for each mouse with an exponential function (*Methods*). Consistent with the behavioral results, we found asymmetric adaptation in the neural responses, with larger adaptation time constants in low contrast (*Mdn* = 0.14, *IQR* = 0.21) relative to high contrast (*Mdn* = 0.033, *IQR =* 0.16;Wilcoxon sign-rank test (n = 8): *rank*  = 28, *Z* = nan, *p* = 0.016).

*Cortical gain predicts behavioral performance.*

Our behavioral results and model provide strong evidence that gain control in the auditory system shapes patterns of behavioral performance. To assess the role of cortical gain in behavior, we leveraged the design of our background sounds to estimate the STRFs and nonlinearities of neurons recorded while mice performed the task. For each neuron, we fit a model with a static nonlinearity (static-LN) or a model with gain control (GC-LN; Figure 6a).

Figure 6b-d plots data from a representative neuron recorded during behavior. The estimated STRF for this example unit is shown in Figure 6c with the nonlinearities estimated for each model in Figure 6d. The fits of the GC- and static-LN models to the data are plotted in the bottom of Figure 6b. We first compared the cross-validated performance of the static-LN model versus the GC-LN model, finding higher correlations using the GC-LN model (*Mdn* = 0.81, *IQR* = 0.17), relative to the static-LN model (*Mdn* = 0.67, *IQR* = 0.12; Wilcoxon sign-rank test (n = 2,792 neurons): *rank* = 3.84e5, *Z* = -36.75, *p* = 1.20e-295; Supplemental Figure 5h). After pooling all of the neurons recorded across all mice and sessions, and including only neurons with strong stimulus responses in both contrasts (*Online Methods*), we observed significantly higher gain in low contrast (*Mdn* = 0.099, *IQR* = 0.13) than in high contrast (*Mdn* = 0.041, *IQR* = 0.023; Wilcoxon sign-rank test (n = 2,792 neurons): *rank* = 3.57e6, *Z* = 38.03, *p* = 2.15e-316; Figure 6e, inset). These results demonstrate that LN models incorporating contrast gain control can more accurately predict cortical activity, and confirm previous reports of robust gain control in ferret and mouse auditory cortex14,17.

Based on our previous results, we predicted that the amount of gain in auditory cortex would predict target detection ability. When fitting the GC-LN model, we separately estimated neural gain during the adaptation period of the trial and the target period of the trial (Figure 6b). To quantify the effects of contrast and trial period on gain, we performed a two-way ANOVA, with gain as the dependent variable, and contrast, trial period, and their interaction as factors. As expected from previous results, we found a significant main effect of contrast (*F*(1,4540) = 441.90, *p* = 1.066e-93). Furthermore, there was a main effect of trial period (*F*(1,4540) = 34.84, *p* = 3.85e-9) and an interaction between contrast and trial period (*F*(1,4540) = 78.94, *p* = 9.051e-19). Post-hoc tests revealed that, in low contrast, gain during the target period increased by 0.032 [0.024, 0.040] (*p* = 3.77e-9), but did not change in high contrast (-0.0065 [-0.014, 0.0014], *p* = 3.77e-9; Figure 6e). These findings indicated that neural gain is not only sensitive to stimulus contrast, but appears to be greater during the target period of the task.

To visualize the gross relationship between gain and psychometric performance, we first averaged the gain of stimulus-responsive neurons during the target period of the task (ie. the time window after the contrast switch) for each session. We then selected only low contrast sessions and split the data by the median gain in the target period, computing the average psychometric curves for sessions in the bottom 50th percentile of gain and those in the top 50th percentile (Figure 6f, inset). We observed that sessions with high gain had steeper slopes and lower thresholds (Figure 6f). To quantify this relationship between gain and task performance, we fit a mixed-effects model using contrast and gain during the target period as fixed effects, mouse identity as a random effect and either psychometric slopes or thresholds as the dependent variable. This approach allowed us to separate the behavioral impact of gain control from effects of session-to-session fluctuations in gain (for full results of the following models, see Supplemental Table 1).

To test the effects of contrast and gain on psychometric thresholds, we fit the full model, as described above. Then, to assess whether the inclusion of session-to-session variability in gain improved the model fit, we compared the full model to a null model which only included contrast. We found that the model including gain was a better predictor of behavioral threshold than the null model (Likelihood Ratio Test: (1) = 4.74, *p* = 0.029), indicating that thresholds decreased by about 2.59 dB SNR ±1.18 (standard error) for every 10% increase in gain. Using a similar procedure, we found that contrast was also a significant predictor of behavioral threshold (Likelihood Ratio Test: (1) = 5.84, *p* = 0.016), with the step from low to high contrast inducing a decrease in behavioral thresholds of 3.01 dB SNR ±1.23 (standard error).

We applied the same analysis to test the effects of contrast and gain on psychometric slopes (Figure 6f), again finding that gain significantly predicted psychometric curves (Likelihood Ratio Test: (1) = 5.09, *p* = 0.024), where the psychometric slope increased by 0.13 dB/PC ±0.059 (standard error) for every 100% increase in gain. However, contrast did not significantly improve the fit of this model (Likelihood Ratio Test: (1) = 1.57, *p* = 0.21). This result is not entirely unexpected, given that we observed no effect of contrast on psychometric slopes when comparing across sessions with different target distributions (Supplemental Figure 2b), which is true of the sessions used in this analysis.

Our findings suggest that the relationship between gain and psychometric performance is shaped by two sources: contrast-induced gain control and by spontaneous fluctuations in gain from session to session. To further disentangle the relationship between these two sources of behavioral modulation, we repeated the mixed effects models, but examined gain during the adaptation period as the predictor of interest. We hypothesized that gain in this period should not be predictive of behavioral performance, as there were no targets presented during this portion of the trial. We found that this was the case and did not observe any predictive relationship between gain during this period and behavioral performance (Supplemental Figure 5i-k; Supplemental Table 1). In summary, we used a linear-nonlinear model to measure cortical gain in behaving mice, finding robust gain control in line with previous findings. Furthermore, we found that gain increased in the target period of the trial, and that psychometric performance is predicted by both the stimulus contrast and by session-to-session changes in cortical gain during target detection.**Discussion**

On a daily basis, we navigate through many auditory environments, each defined by different statistical properties. The dynamic range, or contrast, of acoustic inputs poses a challenge to the auditory system, which is composed of neurons with limited dynamic range in their response. The efficient coding hypothesis predicts that as acoustic contrast shifts, neurons throughout the auditory pathway adjust their sensitivity in order to match the dynamic range of their response to that of the stimulus distribution1. Multiple studies have demonstrated that indeed, neurons throughout the auditory pathway exhibit contrast adaptation14–17. Whereas recent work has demonstrated a link between efficient cortical codes and human psychophysical performance24, whether neuronal contrast adaptation plays a role in auditory perception has not been previously examined simultaneously with behavior.

In this study, we directly linked neuronal contrast gain control to auditory behavior through the use of a theoretical model of efficient coding, behavioral psychophysics, and simultaneous manipulation and recordings of cortical activity. First, we developed a normative framework based on efficient coding20,30 which predicted that: (1) Detection thresholds of targets should be lower in low contrast than in high contrast; (2) Sensitivity to changes target volume should be greater in low contrast relative to high contrast; and (3) Detection should adapt asymmetrically: improving slowly after a switch to low contrast, but decreasing rapidly after a switch to high contrast (Figure 1). Then, we confirmed that gain control dynamics in auditory cortex are indeed asymmetric, using a novel variant of Poisson GLM. To test the model predictions behaviorally, we trained mice to detect a target in background noise as the contrast of the background shifted between high and low contrast. As predicted by the model, mice had lower detection thresholds and were more sensitive to changes in target volume during low contrast. Behavioral adaptation was also asymmetric, decreasing rapidly after a switch to high contrast, and increasing slowly after a switch to low contrast, in agreement with our model and previous theoretical models19 (Figure 3). Furthermore, we found that AC is necessary specifically for this detection-in-noise task (Figure 4). When recording in AC, found that the parameters of neurometric functions were predictive of psuchometric functions on a mouse-to-mouse basis, and also showed that target discriminability adapted asymmetrically, as expected (Figure 5). Finally, we found that cortical gain during the target period of the task could predict behavioral thresholds and slopes on a session-to-session basis, independently of the effect of contrast (Figure 6). Taken together, these results support our hypothesis that efficient coding at the neuronal level shapes auditory behavior.

*The role of cortex in behavior.*

The role of auditory cortex in auditory behavior has been subject of debate. A number of prior studies found that auditory cortex was not required for relatively simple behavioral tasks such as frequency discrimination or detection31,32. Rather, many studies found that auditory cortex is primarily involved in more complex behaviors, such those requiring temporal expectation33, localization34, or discrimination of more complex sounds35–37. Consistent with previous findings38, we found that AC inactivation selectively impaired the detection of targets in a noisy background, but did not impair detection of targets in silence (Figure 4). Furthermore, on a subject-by-subject basis, neuronal activity in AC was correlated with behavioral performance of the subject (Figures 5, 6). This set of results establishes that AC is necessary for the detection of targets in background noise and supports the more general notion that AC is required for more difficult auditory tasks.

While the previous work demonstrates the necessity of auditory cortex in behavioral performance, the brain areas and mechanisms supporting the transformation from stimulus to decision are an active field of study39,40. By recording during the task, we were able to leverage behavioral variability to show that behavioral performance covaried with representations of targets within small neural populations (Figure 5), and with cortical gain (Figure 6). There is a large body of literature relating cortical codes to behavioral variability: early studies in the visual system suggested that information from relatively small numbers of neurons was sufficient to match or outperform animal behavior in psychophysical tasks41–43 and that behavioral choice can be predicted from activity in sensory areas29,43. These accounts suggest that variability in bottom-up sensory encoding drives the variability in behavioral output. However, more recent work suggests that variability in sensory areas is driven by top-down influences44–47, which are modulated by attention and learning48–51. Interestingly, a recent study imaging tens of thousands of neurons in the visual cortex demonstrated that cortical representations had higher acuity than behaving mice, yet did not correlate with behavioral performance, suggesting that perceptual discrimination depends on post-sensory brain regions52.

Our results suggest that bottom-up adaptation to stimulus statistics shapes behavioral output: We observed asymmetric time courses of target discrimination following a change in contrast (Figure 3) which were qualitatively consistent with the predictions of efficient coding (Figure 1), resembled temporal asymmetries of gain adaptation in auditory cortex in the absence of behavior (Figure 2), and resembled patterns of target-driven activity in auditory cortex during the task (Figure 5). Indeed, there have been other studies demonstrating that individual differences in sensory-guided behaviors are reflected in cortical activity53,54, are bidirectionally modulated by cortical manipulation55,56, and can be predicted from tuning properties in auditory cortex57,58. While our results cannot rule out top-down input as the causal driver of sensory decisions, they do support the notion that the sensory information upon which decisions are made is shaped by neuronal adaptation, which thus affects behavioral outcomes.

*Roles of gain in the auditory system.*

Neurons throughout the auditory system adapt to the statistics of the acoustic environment, including the distribution of stimuli over time59,60, more complex sound patterns27,61, and task-related or rewarded stimuli62–67. Inspired by the latter studies, we intentionally designed our stimuli using unbiased white-noise backgrounds, which allowed us to fit encoding models to our data. Using these methods, we focused on contrast gain control as a fundamental statistical adaptation that relates to efficient coding14,17,18,24. In this study, we developed a novel form of Poisson GLM that allowed us quantify the contribution of multiplicative interactions between the stimulus and stimulus contrast to the activity of neurons in auditory cortex. Using the fitted parameters of the model, we were able to accurately estimate neuronal gain as a function of time. This approach allowed us to verify that gain adaptation in auditory cortex is asymmetric (Figure 2), as predicted from efficient coding theory19 and as shown in previous work25.

Furthermore, we found that behavioral detection of targets adapted asymmetrically (Figure 3), similar to observed gain adaptation in auditory cortex. This suggested that the dynamics of contrast gain control influenced task performance. Indeed we found that both stimulus contrast and session-to-session fluctuations in gain predicted psychometric performance (Figure 6). These results suggest two sources of gain modulation in auditory cortex: 1) Bottom-up adaptation to stimulus statistics (ie. contrast gain control), and, 2) session-to-session modulation of gain. Previous studies have demonstrated this latter phenomenon, suggesting that top-down gain modulation underlies attention44,45,68 and optimal behavioral states69,70. Our results suggest that automatic forms of gain control as well as session-to-session fluctuations in gain both modulate behavior, and provide a starting point for dissecting the neural mechanisms underlying these two forms of gain modulation.

*Cellular mechanisms of gain control.*

While this and other studies demonstrated contrast gain control in the auditory system, the neuronal mechanisms driving gain adaptation at a cellular level remain unclear. In the current study, we have likely recorded from a mixed population of excitatory and inhibitory neurons. Different inhibitory neuronal subtypes exhibit specific roles in adaptation71,72. Although specific inhibitory neuronal subtypes facilitate divisive or subtractive control of excitatory responses in visual73,74 and auditory cortex75,76, the role of these interneurons in contrast gain control has been inconclusive18. Furthermore, we were able to separate the behavioral contribution of contrast gain control from stimulus-invariant changes in gain. Whether these two forms of gain control share common neural substrates is unclear. By combining previously mentioned optogenetic methods with behavioral tasks, future studies may explore and test the specific role of local circuits and top-down modulation in gain control and behavior.

*The missing link between efficient coding and behavior.*

Combined, our results develop a framework and provide support for the role of efficient neuronal coding in behavior. The efficient coding hypothesis has emerged as one of the leading principles in computational neuroscience that has shaped our understanding of neuronal coding, architecture and evolution1,21,77–79. Prior research found that human behavior follows principles of efficiency23,24. Our work now provides a framework for linking the principles of neuronal coding with behavioral performance. Additionally, we have introduced a novel form of Poisson GLM designed to detect multiplicative interactions between presented stimuli and other variables. While in this study we focused on the multiplicative effect of contrast, this approach could in theory be applied to any other time-varying signal that modulates neuronal gain, such as movement80,81, arousal69,70, or targeted experimental interventions74–76,82. In summary, we expect the theoretical frameworks and modelling methods applied here to have broad utility in the study of neuronal adaptation, a fundamental function of the nervous system.