Learning-induced changes in auditory processing: An MEG investigation using an active learning task and oddball paradigm

Grigory Kopytin
Institute for Cognitive Neuroscience
HSE University
Moscow, Russia
gkopytin@hse.ru

Alla Kondratenko
Institute for Cognitive Neuroscience
HSE University
Moscow, Russia
aakondratenko_3@edu.hse.ru

Viktoria Moiseeva
Institute for Cognitive Neuroscience
HSE University
Moscow, Russia
vmoiseeva@hse.ru

Anna Shestakova
Institute for Cognitive Neuroscience
HSE University
Moscow, Russia
a.shestakova@hse.ru

Abstract—**The present study investigated the effects of an active learning task on rapid plasticity in auditory processing using an oddball paradigm combined with magnetoencephalography (MEG). Twenty-nine healthy participants completed two passive oddball tasks, with an active one-armed bandit learning task between them. We analyzed the mismatch negativity (MMN), P3a, and late positive potential (LPP) components of the event-related fields to assess learning-induced changes in auditory processing. While the active learning task did not significantly enhance the amplitudes of these components, we found a significant correlation between learning performance and changes in the P3a component. Specifically, better learning of the associations between sounds and monetary outcomes was related to a decrease in P3a amplitude for the optimally learned sound. These findings suggest that the P3a component may serve as a neural marker of rapid, learning-induced plasticity in auditory processing. Our study contributes to the understanding of the dynamic nature of auditory processing and its relationship to learning and decision-making, with potential applications in educational and clinical settings.**

Keywords—cortical plasticity, MMN, MEG, decision-making

I. Introduction

The human brain demonstrates a remarkable ability to adapt to environmental demands through experience-induced plasticity. Training can lead to the reorganization of cortical maps and the establishment of interconnections among specific cortical and subcortical areas [1,2]. This directed cortical plasticity [3] is essential for learning and memory formation.

One of the most widely used tools to study training-induced plasticity in the auditory domain is the mismatch negativity (MMN) component of the event-related potential. MMN reflects the brain's automatic detection of changes in the environment [4,5] and is modulated by experience and training [6-12], making it a valuable tool for investigating the neural correlates of learning-induced plasticity.

Recent studies have shown that the sensory cortex participates in learning during classical conditioning [13] and that reward-associated plasticity can occur across different sensory modalities. Gorin et al. [14] found an enhanced MMN response to incentive cues predicting large monetary losses, which correlated with the feedback-related negativity (FRN), a neural signature of reinforcement learning [15,16,17,18].

Building upon these findings, the present study aims to further investigate the neural correlates of training-induced plasticity in the context of economic decision-making. We employed a similar auditory paradigm, but with two key modifications. First, we used an active learning task (one-armed bandit) instead of the passive monetary incentive delay (MID) task to assess the effects of a more engaging learning experience on auditory cortical plasticity. Second, we focused on the rapid, within-day changes in auditory processing induced by the active learning task, rather than the overnight consolidation effects explored in the previous study.

We hypothesized that the active learning task would induce rapid plastic changes in the cortex, reflected by enhanced MMN, P3a, and LPP responses to auditory cues associated with monetary losses. By comparing the neural responses before and after the learning task, we aimed to investigate the effects of active learning on auditory processing and its potential relationship with economic decision-making. Furthermore, we anticipated that these plastic changes would occur rapidly, within a single experimental session, without the need for an overnight consolidation period.

II. Methods

A. Participants

Twenty-nine healthy, right-handed participants (16 females, aged between 18 and 56 y.o., mean age = 23.7, sd = 6.6) with normal or corrected-to-normal vision participated in the study. All participants signed an informed consent form before the experiment.

B. Stimuli

The stimuli were eight pure monotone sounds with fundamental frequencies of 272, 325, 381, 440, 502, 568, 637, and 711 Hz, generated using PRAAT software. Each sound was 200 ms long and had an intensity of 70 dB.

C. Experimental Design

The experiment consisted of two identical sessions of a roving oddball paradigm, with a punishment-based learning task between the sessions.

During the roving oddball task, participants were exposed to auditory stimuli through headphones at a fixed intensity of 70 dB while viewing a neutral video. The stimuli were presented in a roving oddball sequence, where each sound was repeated 4-6 times consecutively before transitioning to the next sound. The order of the sounds was randomized, with the constraint that consecutive sounds were separated by 1 to 3 frequency steps (an average of 120 mel or two steps). The first presentations of a specific frequency within each series were considered deviants, while the final repetitions were considered standards. The task involved 1400 stimulus presentations lasting approximately 24 minutes, with each stimulus type (deviant/standard) being presented around 35 times for each frequency.

The learning task was a dynamic one-armed bandit monetary punishment-based learning task with changing choice options. Each participant was randomly assigned to four pairs of sounds (sound contrasts) constructed from the sounds used in the roving oddball task. In each contrast, each sound was randomly assigned to either a small (SL) or big loss (BL) condition. The small loss condition was characterized by monetary losses randomly selected from a normal distribution with a mean of 5 and a standard deviation of 20, while the big loss condition was characterized by losses from a distribution with a mean of 50 and a standard deviation of 20. Each trial started with an endowment of 60 coins. Participants were sequentially presented with two sound contrasts, with a "sound icon" accompanying the presentation of each sound on the left (first sound) and right (second sound) side of the screen. They were then prompted to choose either the sound presented first (left icon) or second (right icon), after which the monetary outcome was revealed. The outcome for each trial was calculated by subtracting a condition-specific randomly selected loss from the initial endowment of 60 coins, followed by the start of a new trial. The outcome was the initial 60 coins minus a value randomly selected from the condition's distribution, and then a new trial began. There were no probabilistic relationships between the sounds and monetary outcome conditions. Before the experiment, participants were instructed to learn which sounds led to small and big losses and to make choices that maximized their average monetary outcome. They were told that they would be paid depending on the average monetary outcome, providing additional motivation. The task included 200 trials (50 per sound contrast, or block) and lasted approximately 30 minutes.

After participants established the association between sounds and monetary outcomes during the learning task, they were exposed to the same auditory stimuli a second time (session two of the roving oddball paradigm), which allowed to assess condition-specific (small vs. big loss) fast training-induced changes in the brain.

D. MEG Recording and Processing: Passive Oddball Tasks

MEG signals of brain-induced responses were recorded using a 306-channel MEG setup (Neuromag, Helsinki, Finland), with head movements tracked by a head position indicator with four coils throughout the entire experiment, along with horizontal and vertical electrooculogram (EOG) and electrocardiogram (ECG) to detect physiological artifacts.

Further processing of the MEG data was performed using MNE-Python [19] and custom Python scripts. To minimize the influence of external magnetic field noise and technical artifacts, the raw MEG data were pre-processed using the tSSS algorithm [20] and simultaneous correction for head movement.

Gradiometer data were taken for subsequent analysis, resampled (250 Hz), band-pass filtered (0.5–45 Hz), and eye and heart artifacts were removed using independent component analysis (FastICA).

Preprocessed and artifact-cleaned data were epoched into segments of -100 to 900 ms relative to the stimulus onset. MMN subtraction (first presentation of a stimulus in a series minus final repetition) was performed for each oddball series and averaged across stimulus conditions, resulting in a total number of approximately 35 MMN responses per sound frequency condition.

To select specific clusters of channels and time windows for subsequent analysis, root mean square (RMS) values were calculated for planar gradiometer data. Visual assessment revealed three time windows of interest: MMN (100-200 ms), P3a (200-300 ms), and LPP (Late Positive Potential) (400-650 ms). Subsequently, topographic responses of the gradiometers were plotted for the time points corresponding to the peak values within the identified time windows, and specific cluster of channels was chosen (Figure 1A). RMS values of the gradiometers within the selected clusters and time windows for each oddball session are shown in Figure 1B.

Finally, the difference between the second and first oddball sessions was calculated for the mean values in each time window for each condition and subject (ΔMean RMS values), serving as a measure of training-induced plasticity.

E. Behavioural Responses: Reinforcement Learning Task

Our general measure of learning was the rate of 'correct' responses (RCR). Responses were treated as 'correct' if a participant chose the sound that led to the small loss condition, thus, postulating the best (correct) option among two possible ones. RCR was calculated for each block and each subject.

F. Statistical analysis

To track changes associated with the specific sound conditions (small and big loss) in the MMN, P3a and LPP components, we first ensured that mean RMS responses differed between the two oddball sessions. For this, we ran a repeated-measures ANOVA with the mean RMS values as the independent variable, and oddball (2 levels: oddball 1, oddball 2) and condition (2 levels: small loss, big loss) as the dependent variables.

After this, to assess how strongly the training-induced changes in each of the event-related fields (ERF) components (MMN, P3a, LPP) are explained by each of the loss conditions, we correlated (spearman correlation) these changes (ΔMean RMS values) for sounds associated with the small loss and big loss conditions, respectively, with the RCR.
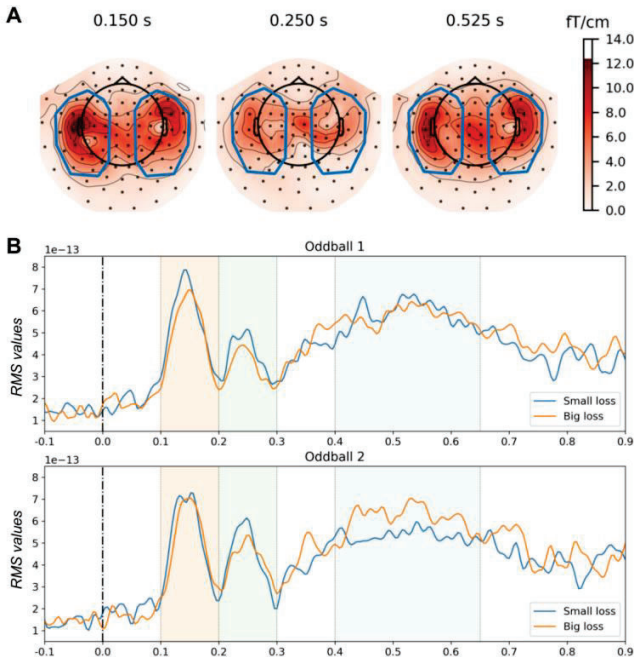
Fig 1. Topographic and temporal characteristics of responses to oddball stimuli under different loss conditions. **(A)** Topography of the peak MMN (left), P3a (middle) and LPP (right) responses. Global average of the calculated mismatch negativity (MMN) responses, planar gradiometers. The blue line corresponds to the manually selected cluster of sensors that will be used for further analysis. **(B)** RMS values of the selected gradiometer sensors calculated for the mismatch negativity responses for the first (upper) and second (lower) oddball sessions. The blue line corresponds to the small loss condition, while the orange one corresponds to the big loss condition. The shaded areas on the graph correspond to the time windows selected for further analysis: orange for the MMN (100-200ms) time window, green for the P3a (200-300ms), and blue for the LPP (400-650ms).

III. RESULTS

Repeated-measures ANOVA showed oddball to be a significant predictor for ΔMean RMS values in all of the ERF components ($F_{(1, 344)} = 5.80$, $p = 0.016$; $F_{(1, 344)} = 7.23$, $p = 0.007$; $F_{(1, 344)} = 9.07$, $p = 0.002$, respectively for MMN, P3a, and LPP), while neither condition nor the oddball:condition interaction were significant. These statistical results imply that plasticity effects are observed in all time windows in general, without showing specificity for the loss condition, which contradicts our hypothesis postulating this specificity.

Nonetheless, differences in brain responses between oddballs could be explained by or correlated with learning outcomes, possibly showing specificity for the loss condition. To investigate this, we used Spearman correlation to assess relationships between ΔMean RMS values for sounds associated with the small loss and big loss conditions and the rate of 'correct' responses in the learning task. Results are demonstrated in Figure 2.

Overall, while active learning does not seem to enhance brain responses in any of the sensory (MMN), attentional (P3a), or cognitive (LPP) domains, it can indeed explain some of the variance in the overall changes in the P3a component before and after learning. Specifically, the better participants learn the association between the sound and monetary outcome, choosing

the most optimal option for maximizing rewards, the lower their P3a amplitude is to the optimally learned sound.
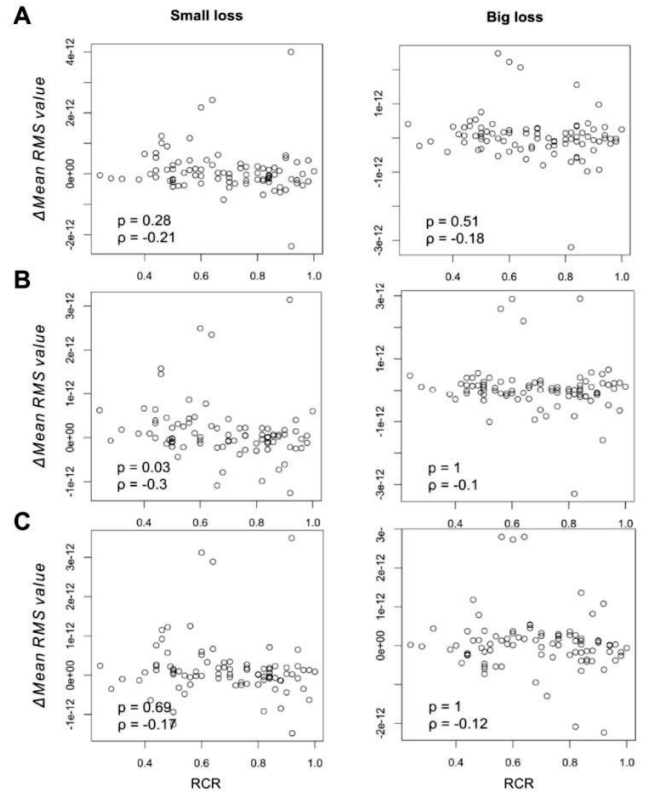

Fig. 2. Correlation analysis of the changes in brain response (ΔMean RMS values, y-axes) and learning performance (RCR, x-axes) for sounds associated with small or big loss in three event-related fields components. Spearman correlation, all p-values are Bonferroni adjusted. **(A)** Changes in MMN between oddball sessions for small and big loss conditioned sounds do not correlate with performance in the learning task ($p = 0.28$, $\rho = -0.21$, and $p = 0.51$, $\rho = -0.18$ for small and big loss conditions, respectively). **(B)** Changes in P3a between oddball sessions significantly correlate ($p = 0.03$, $\rho = -0.3$) with performance in the learning task for the small loss condition, but do not correlate ($p = 1$, $\rho = -0.1$) for the big loss condition. **(C)** Changes in LPP between oddball sessions for small and big loss conditioned sounds do not correlate with performance in the learning task ($p = 0.69$, $\rho = -0.17$, and $p = 1$, $\rho = -0.12$ for small and big loss conditions, respectively).

IV. DISCUSSION

The present study investigated the effects of an active learning task on rapid plasticity in the auditory processing using an oddball paradigm. We found that the active learning task did not significantly enhance the amplitudes of the MMN, P3a, or LPP components. However, the learning performance correlated with the changes in the P3a component, suggesting that the P3a may serve as a neural marker of learning-induced plasticity in auditory processing.

The P3a component is thought to reflect attentional orienting towards novel or salient stimuli and is considered to have a frontal origin [21]. In our study, better learning of the association between sounds and monetary outcomes was related to a decrease in P3a amplitude for the optimally learned sound. This finding is consistent with previous studies showing that the P3a amplitude is modulated by stimulus familiarity and learning [22,23]. The reduction in P3a amplitude for the optimally

learned sound may indicate a decrease in the novelty or salience of this stimulus as a result of learning.

Contrary to our hypothesis, we did not observe significant learning-related changes in the MMN component. The MMN is an index of automatic auditory change detection [4,5] and has been shown to be sensitive to training-induced plasticity [6-12]. The absence of significant MMN changes in our study may be due to the rapid nature of the learning task, which might not have been sufficient to induce detectable changes in early sensory processing. Additionally, the lack of an overnight consolidation period, which has been shown to enhance MMN changes following learning [24], may have contributed to the absence of significant MMN effects.

The LPP component, which reflects higher-order cognitive processing and is sensitive to the emotional significance of stimuli, also did not show significant learning-related changes in our study. This suggests that the active learning task may not have significantly modulated the emotional or motivational salience of the auditory cues, at least not in a way that was detectable by the LPP.

It is important to note that our study focused on rapid, within-day plasticity induced by an active learning task, whereas previous studies have often investigated longer-term plasticity effects over multiple days or weeks [7,8,12]. The different time scales of plasticity investigated may account for some of the discrepancies between our findings and those of previous studies.

In conclusion, our study demonstrates that an active learning task can induce rapid plasticity in auditory processing, as reflected by the correlation between learning performance and changes in the P3a component. These findings contribute to our understanding of the dynamic nature of auditory processing and its relationship to learning and decision-making. Future studies should investigate the long-term effects of active learning on auditory plasticity and explore the potential applications of these findings in educational and clinical settings.

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