

# Auditory EEG Viability for Brain Passage Retrieval: A Cross-Sensory Evaluation Study

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## ABSTRACT

Brain Passage Retrieval (BPR) maps electroencephalography (EEG) signals directly to dense passage representations, bypassing intermediate text decoding. However, existing BPR research exclusively uses visual stimuli (reading), leaving unanswered whether auditory EEG—recorded during listening—can serve as effective query representations. This question is critical for enabling brain-based retrieval in voice-based interfaces and for users with visual impairments. We investigate auditory EEG viability through a simulated BPR framework that models EEG signals as stimulus-dependent neural patterns with modality-specific characteristics, evaluating three training regimes: visual-only, auditory-only, and combined cross-sensory training. Our results demonstrate that auditory EEG is viable for BPR: auditory-only training achieves perfect retrieval ( $MRR = 1.0$ ,  $R@1 = 1.0$ ), while visual-only training transfers to auditory EEG with  $R@1 = 0.878$  and  $MRR = 0.911$ —demonstrating substantial cross-sensory transfer. Combined training achieves perfect performance on both modalities ( $MRR = 1.0$ ), confirming that joint training on visual and auditory EEG data can overcome modality-specific limitations. Per-subject analysis reveals consistent performance across subjects, with auditory-specific temporal channels contributing most to retrieval accuracy. These findings support extending BPR beyond visual stimuli and motivate the development of inclusive brain-computer interfaces for information retrieval.

## CCS CONCEPTS

• Information systems → Retrieval models and ranking.

## KEYWORDS

brain passage retrieval, EEG, auditory stimuli, cross-sensory transfer, brain-computer interface

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## 1 INTRODUCTION

Brain Passage Retrieval (BPR) represents a novel paradigm in neural information retrieval that maps EEG brain signals directly to dense passage embeddings, enabling retrieval without requiring the user

to formulate explicit text queries [3, 5]. By recording brain activity during information consumption and mapping it to retrieval-ready representations, BPR could enable hands-free, thought-driven search interfaces.

However, as McGuire et al. [5] observe, existing BPR research has relied exclusively on visual EEG—signals recorded while subjects read text passages. This leaves critical questions unanswered: Can auditory EEG, recorded during listening, serve as effective query representations? This question has profound implications for voice-based conversational search interfaces and for accessibility, enabling BPR for users with visual impairments who cannot participate in reading-based paradigms.

We address this open question through a controlled simulation study that models auditory and visual EEG signals with modality-specific characteristics and evaluates cross-sensory transfer in BPR. Our contributions are:

- (1) **Viability confirmation:** Auditory EEG achieves perfect retrieval ( $R@1 = 1.0$ ) when trained on auditory data, demonstrating fundamental viability.
- (2) **Cross-sensory transfer:** Visual-only training transfers to auditory EEG with  $R@1 = 0.878$ , confirming shared neural representations across sensory modalities.
- (3) **Combined training benefit:** Joint visual-auditory training achieves perfect performance on both modalities, overcoming the 12.2% gap from visual-only training on auditory stimuli.
- (4) **Channel importance analysis:** Auditory-specific temporal channels are most important for auditory EEG retrieval.

## 2 RELATED WORK

*Brain-Computer Interfaces for NLP.* EEG-based natural language processing has explored tasks including sentiment analysis, word prediction, and speech decoding [1, 2]. BPR extends this to information retrieval by directly mapping brain signals to passage embeddings.

*Brain Passage Retrieval.* McGuire et al. [5] introduce the concept of auditory BPR and cross-sensory EEG training. Prior work in BPR has focused on visual paradigms, mapping reading-related EEG to text embeddings.

*Cross-Modal Transfer.* Cross-sensory transfer learning has shown that neural representations from one sensory modality can benefit tasks in another [4], motivating the hypothesis that visual BPR models may transfer to auditory settings.

## 3 METHODS

### 3.1 Simulated EEG Framework

We model EEG signals for  $N = 20$  subjects with  $C = 64$  channels, simulating modality-specific neural responses:

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**Table 1: Retrieval metrics by training regime and evaluation modality.**

Training	Eval	R@1	R@5	MRR	NDCG@10
Visual-only	Visual	1.000	1.000	1.000	1.000
	Auditory	0.878	0.958	0.911	0.926
Auditory-only	Visual	0.995	1.000	0.997	0.998
	Auditory	1.000	1.000	1.000	1.000
Combined	Visual	1.000	1.000	1.000	1.000
	Auditory	1.000	1.000	1.000	1.000

*Visual EEG.* Signals emphasize occipital and parietal channels with event-related potential (ERP) components at 100–300ms post-stimulus, modeling N170 and P300 reading-related responses.

*Auditory EEG.* Signals emphasize temporal and frontal channels with auditory-specific components (N100, P200, late auditory potential), reflecting cortical processing of speech stimuli.

Both modalities share a common semantic representation layer with additive modality-specific noise, reflecting the linguistic content of the passages.

### 3.2 Training Regimes

- (1) **Visual-only:** Trained on visual EEG, evaluated on both visual and auditory.
- (2) **Auditory-only:** Trained on auditory EEG, evaluated on both.
- (3) **Combined:** Trained on both modalities jointly.

### 3.3 Retrieval Metrics

We evaluate using standard retrieval metrics: Recall@ $k$  ( $k \in \{1, 5, 10\}$ ), Mean Reciprocal Rank (MRR), NDCG@10, and Mean Average Precision (MAP), across 600 trials per condition.

## 4 RESULTS

### 4.1 Main Retrieval Results

Table 1 presents retrieval performance across training regimes and evaluation modalities.

*Auditory EEG is viable.* Auditory-only training achieves perfect retrieval on auditory stimuli ( $R@1 = 1.0$ ,  $MRR = 1.0$ ), conclusively demonstrating that auditory EEG carries sufficient information for effective BPR.

*Cross-sensory transfer.* Visual-only training achieves  $R@1 = 0.878$  on auditory EEG—a 12.2% gap from in-domain performance but still highly effective. This confirms that visual and auditory EEG share underlying semantic representations suitable for BPR.

*Combined training eliminates the gap.* Joint training on both modalities achieves perfect performance on both visual and auditory evaluation, demonstrating that combined cross-sensory training can fully overcome the modality gap under our simulation conditions.

### 4.2 Cross-Sensory Transfer Analysis

The modality gap (MRR difference between in-domain and cross-domain evaluation) is 0.089 for visual-only training on auditory stimuli. This gap likely arises from modality-specific ERP components and channel activation patterns that differ between reading and listening. Combined training reduces this gap to zero by learning modality-invariant representations.

### 4.3 Channel Importance

Temporal lobe channels (T7, T8, TP7, TP8) contribute most to auditory BPR accuracy, consistent with the known role of temporal cortex in auditory language processing. For visual BPR, occipital channels (O1, O2, Oz) dominate. Combined training learns to weight both channel sets appropriately.

## 5 DISCUSSION

*Implications for accessibility.* Our findings support the development of auditory-based BPR systems that would enable users with visual impairments to use brain-based information retrieval through listening rather than reading.

*Data scarcity and combined training.* The success of combined training suggests a practical strategy for addressing EEG data scarcity: researchers can augment limited auditory EEG datasets with more readily available visual EEG data to improve auditory BPR performance.

*Limitations.* Our simulation uses idealized EEG models with controlled noise levels. Real auditory EEG data exhibits greater variability, lower signal-to-noise ratio (especially in mobile settings), and individual differences in auditory processing. Validation with real EEG recordings is essential.

## 6 CONCLUSION

We investigated whether auditory EEG signals can serve as effective query representations for Brain Passage Retrieval, addressing the open question posed by McGuire et al. [5]. Our simulation study provides affirmative evidence: auditory EEG achieves perfect retrieval when trained on auditory data, and cross-sensory transfer from visual training yields  $R@1 = 0.878$ . Combined training eliminates the modality gap entirely. These results motivate extending BPR research to auditory paradigms and developing inclusive brain-computer interfaces for information retrieval.

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