

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

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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:

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

120 Training	121 Eval	122 R@1	123 R@5	124 MRR	125 NDCG@10
126 Visual-only	Visual	1.000	1.000	1.000	1.000
	Auditory	0.878	0.958	0.911	0.926
128 Auditory-only	Visual	0.995	1.000	0.997	0.998
	Auditory	1.000	1.000	1.000	1.000
130 Combined	Visual	1.000	1.000	1.000	1.000
	Auditory	1.000	1.000	1.000	1.000

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

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

137 Both modalities share a common semantic representation layer
 138 with additive modality-specific noise, reflecting the linguistic con-
 139 tent of the passages.

3.2 Training Regimes

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

3.3 Retrieval Metrics

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

4 RESULTS

4.1 Main Retrieval Results

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

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

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

169 *Combined training eliminates the gap.* Joint training on both
 170 modalities achieves perfect performance on both visual and audi-
 171 torily evaluation, demonstrating that combined cross-sensory train-
 172 ing can fully overcome the modality gap under our simulation
 173 conditions.

4.2 Cross-Sensory Transfer Analysis

175 The modality gap (MRR difference between in-domain and cross-
 176 domain evaluation) is 0.089 for visual-only training on auditory
 177 stimuli. This gap likely arises from modality-specific ERP compo-
 178 nents and channel activation patterns that differ between reading
 179 and listening. Combined training reduces this gap to zero by learn-
 180 ing modality-invariant representations.

4.3 Channel Importance

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

5 DISCUSSION

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

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

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

6 CONCLUSION

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

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