MultiDiffNet: A Multi-Objective Diffusion Framework for Generalizable Brain Decoding

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Abstract

Neural decoding from electroencephalography (EEG) remains fundamentally limited by poor generalization to unseen subjects, driven by high inter-subject variability and the lack of large-scale datasets to model it effectively. Existing methods often rely on synthetic subject generation or simplistic data augmentation, but these strategies fail to scale or generalize reliably. We introduce *MultiDiffNet*, a diffusion-based framework that bypasses generative augmentation entirely by learning a compact latent space optimized for multiple objectives. We decode directly from this space and achieve state-of-the-art generalization across various neural decoding tasks using subject and session disjoint evaluation. We also curate and release a unified benchmark suite spanning four EEG decoding tasks of increasing complexity (SSVEP, Motor Imagery, P300, and Imagined Speech) and an evaluation protocol that addresses inconsistent split practices in prior EEG research. Finally, we develop a statistical reporting framework tailored for low-trial EEG settings. Our work provides a reproducible and open-source foundation for subject-agnostic EEG decoding in real-world BCI systems.

1 Introduction

Electroencephalography (EEG) is a widely used modality in brain–computer interfaces (BCIs), supporting applications from assistive communication to cognitive monitoring. Deep learning has improved decoding across motor imagery, SSVEP, and speech tasks [10, 1, 23], yet generalizing to unseen subjects remains challenging due to high inter-subject variability and limited data [14, 4].

Subject-specific models require extensive per-user calibration [11, 27], while multi-subject models struggle to generalize [31, 25, 41]. The alternative is to use two-stage pipelines that generate EEG via GANs or diffusion and then train decoders [11, 37], but they suffer from low realism, artifact transfer, and inefficiencies.

We propose *MultiDiffNet*, a unified multi-objective diffusion framework that learns a shared latent space, eliminating the need for synthetic augmentation and enhancing generalization. To benchmark progress, we release a curated suite spanning SSVEP, Motor Imagery, P300, and Imagined Speech

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tasks, with standardized subject- and session-disjoint evaluation. We also develop a statistical reporting protocol tailored for low-trial EEG research, addressing a persistent gap in reproducibility.
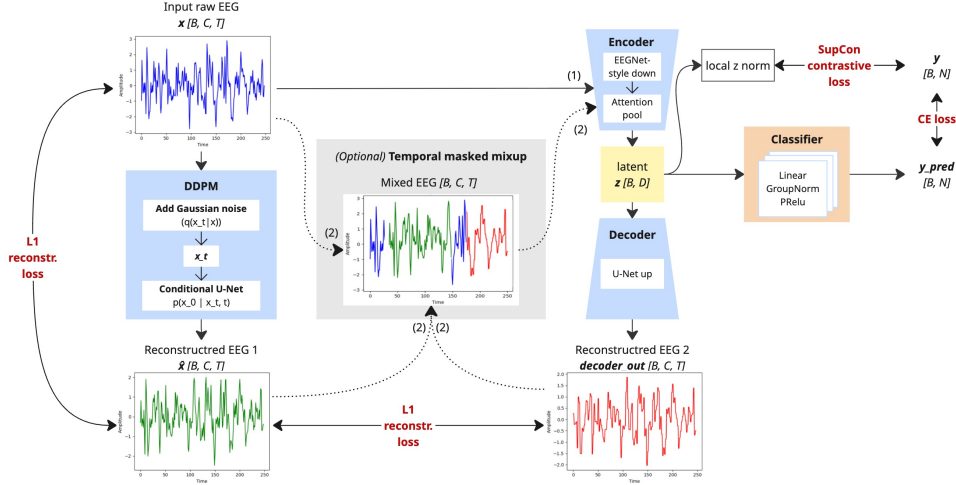

Figure 1: Overview of the *MultiDiffNet* that jointly optimizes a conditional DDPM, a contrastive encoder, and a generative decoder through a shared latent space *z*. The encoder produces discriminative features used for both classification and contrastive learning, while the decoder and DDPM reconstruct the input signal. An optional *temporal masked mixup* module stochastically blends the original, DDPM-denoised, and decoder-reconstructed EEG to improve representation quality.

2   Related work

EEG Decoding and Generalization EEG decoding has evolved from handcrafted features to deep architectures, with EEGNet emerging as a widely adopted baseline due to its efficient depthwise–separable convolutions and lightweight design [22, 44]. Recent models explore transformers [3, 24, 34] and graph neural networks [35, 13], but EEGNet remains favored for its robustness and simplicity. A key limitation is poor cross-subject generalization, with 20-40% accuracy drops despite strong within-subject performance [14, 4]. Attempts to address this require expensive calibration [31, 25, 41]. Scalable BCIs require subject-agnostic models that generalize without per-user retraining.

Diffusion Models for EEG Denoising Diffusion Probabilistic Models (DDPMs) model data distributions via iterative denoising and outperform GANs in EEG synthesis by avoiding mode collapse [38, 12]. Recent enhancements, such as reinforcement learning [2] and progressive distillation [37], have further improved realism and sampling speed. Diff-E [17] extended diffusion to imagined-speech decoding via joint reconstruction and classification, but remained task-specific and did not address cross-subject generalization. Broader research suggests that combining generative and discriminative objectives yields stronger representations [7, 9], yet EEG models typically optimize only one. We explore this joint learning paradigm across diverse EEG tasks, aiming to learn generalizable representations that capture both signal structure and task-relevant information.

Mixup Methods Signal-level augmentation has evolved from basic jittering and filtering to temporal, spectral, and channel-wise mixup [28, 26, 16, 30, 42], but many variants introduce unrealistic artifacts that hinder generalization [5]. This motivates our systematic evaluation of weighted and temporal input mixup across encoder layers, along with latent-space mixing

Evaluation Strategies Effective cross-subject EEG decoding requires both rigorous training strategies and standardized evaluation. Leave-one-subject-out (LOSO) validation remains common but is computationally intensive and impractical for real-time deployment [8, 6, 46, 4, 21], while simpler subject splits often neglect session independence and true seen/unseen separation [43]. We address it in our work by introducing a standardized subject- and session-disjoint evaluation.

3 Methodology

3.1 MultiDiffNet architecture

MultiDiffNet is a modular architecture designed to jointly optimize classification, reconstruction, and contrastive structure learning from EEG signals. It consists of a Denoising Diffusion Probabilistic Model (DDPM), a discriminative encoder, a generative decoder, and a classifier (Figure 1).

Given a raw EEG signal $x \in \mathbb{R}^{C \times T}$, where C is the number of EEG channels and T is the number of timepoints, the model processes the input in two parallel paths. First, the DDPM denoises the signal via a learned reverse diffusion process, producing a refined version $\hat{x} \in \mathbb{R}^{C \times T}$. Simultaneously, the same input x is passed through an EEGNet-based encoder (See Section 3.2) to extract a latent representation $z \in \mathbb{R}^D$, where D is the embedding dimension. The latent vector z is then used for two purposes: (1) it is passed to a lightweight decoder to reconstruct the denoised signal $\hat{x}$, resulting in a reconstruction $x_{\text{dec}} \in \mathbb{R}^{C \times T}$; and (2) it is passed to a fully connected classification head to predict class logits $\hat{y} \in \mathbb{R}^K$, where K is the number of classes.

To further structure the latent space, z is locally normalized (Section 3.3) and then projected to $z_{\text{proj}} \in \mathbb{R}^{D'}$, which is optimized with a supervised contrastive loss. All classification and reconstruction are performed directly from z, without relying on generated augmentations.

We performed an extensive ablation study across architectural variants, modifying the presence of DDPMs, encoder inputs, decoder pathways, classifier heads, and loss terms. The configuration described here reflects the best-performing combination.

3.2 EEGNet-style encoder with attention pool

Given EEGNet's demonstrated effectiveness across multiple EEG decoding tasks, we adapt its architecture as our discriminative encoder, hypothesizing that its proven feature extraction capabilities can produce powerful latent representations z for our multi-objective framework. Our encoder extracts multi-scale features (dn_1, dn_2, dn_3) from different layers and applies attention pooling:

$$z = \text{AttentionPool}(dn_3) \in \mathbb{R}^D,$$

3.3 Subject-wise latent normalization

To mitigate inter-subject variability, we apply subject-wise normalization on the encoder output z:

$$z_{\text{norm}} = \frac{z - \mu_s}{\sigma_s},$$

where μ_s and σ_s denote the mean and standard deviation computed per subject s using a subset of training trials. During evaluation, we adopt a two-mode strategy: for seen subjects, normalization uses pre-computed statistics from their training data; for unseen subjects, statistics are estimated on-the-fly using their own calibration trials, simulating realistic deployment scenarios.

Algorithm 1 Temporal Masked Mixup

1: Initialize a binary mask $M \in \{0, 1\}^{C \times T}$ with all zeros.
2: Flip each 0 in M to 1 with probability $p = 0.01$.
3: **for** each position in M with value 1 **do**
4:     Expand to a temporal window of random length (uniform between min and max size).
5: **end for**
6: Flip each 1 in M to -1 with:
- Fixed probability 0.5 (**fixed ratio**), or
- Probability drawn from Beta$(0.2, 0.2)$ each epoch (**random ratio**).
7: Apply the final mask:
- $0 \rightarrow x$ (original input)
- $1 \rightarrow \hat{x}$ (DDPM output)
- $-1 \rightarrow x_{\text{dec}}$ (decoder output)

3.4 Mixup strategies

Mixup strategies can improve robustness in low-trial EEG decoding. However, standard mixup techniques may not fully exploit the structure of neural time series. We therefore explore two complementary strategies: *Weighted Average Mixup* and a novel *Temporal Masked Mixup*. *Weighted Average Mixup* performs linear interpolation between the original EEG input x, the DDPM-denoised output $\hat{x}$, and the decoder reconstruction x_{dec}. We investigate multiple integration points in the model: **(0)** Input-level mixup, **(1-3)** Mixup after encoder layers 1, 2, or 3, respectively, **(4)** Mixup after the final attention pooling layer. To address the limitations of global interpolation, we propose *Temporal Masked Mixup*, which perturbs only localized segments of the input time series while preserving surrounding structure. See Algorithm 1 for pseudocode.

3.5 Loss functions

MultiDiffNet is trained using a weighted sum of three objectives:

$$\mathcal{L}_{\text{total}} = \underbrace{\alpha\,\mathcal{L}_{\text{CE/MSE}}(\hat{y}, y)}_{\text{classification}} + \underbrace{\beta\,\mathcal{L}_{\text{L1}}(x_{\text{dec}}, \hat{x})}_{\text{reconstruction}} + \underbrace{\gamma\,\mathcal{L}_{\text{SupCon}}(z_{\text{proj}}, y)}_{\text{contrastive}}$$

We fix $\alpha = 1.0$ and progressively scale β and γ to stabilize training:

$$\beta = \min\left(1.0, \frac{\text{epoch}}{100}\right) \cdot 0.05, \quad \gamma = \min\left(1.0, \frac{\text{epoch}}{50}\right) \cdot 0.2$$

Details on loss formulation and weighting strategies are provided in the Appendix.

3.6 Evaluation metrics

We evaluate model performance primarily using downstream classification accuracy, which quantifies the proportion of correctly classified EEG samples. Accuracy is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. In addition, we report F1 score, precision, recall, and AUC for a more comprehensive evaluation; detailed formulas and results are provided in the Appendix.

3.7 Trend-level statistical reporting framework

Conventional p-values often fail under the high-variance, low-trial, subject-disjoint conditions of EEG decoding. To address this, we introduce a robust trend-level statistical framework (detailed in the Appendix) that synthesizes effect sizes, cross-seed consistency, and Bayesian posterior probabilities. This allows us to detect systematic, reproducible gains even when classical significance tests return null results. Our approach represents a principled shift toward reproducible, evidence-based model evaluation in brain decoding. While this framework enhances reproducibility, it is not meant to substitute conventional p-value testing. Instead, it addresses a well-documented limitation: in low-trial, high-variance EEG decoding, even systematic improvements may fail to reach arbitrary significance thresholds.

4 Experiments and results

4.1 Benchmark dataset suite

We curated four diverse EEG benchmarks (SSVEP, P300, Motor Imagery, and Imagined Speech), spanning increasing decoding difficulty. Each dataset is split into train, val, and two test sets: a seen-subject (intra-subject) split and an unseen-subject (cross-subject) split. This standardized protocol
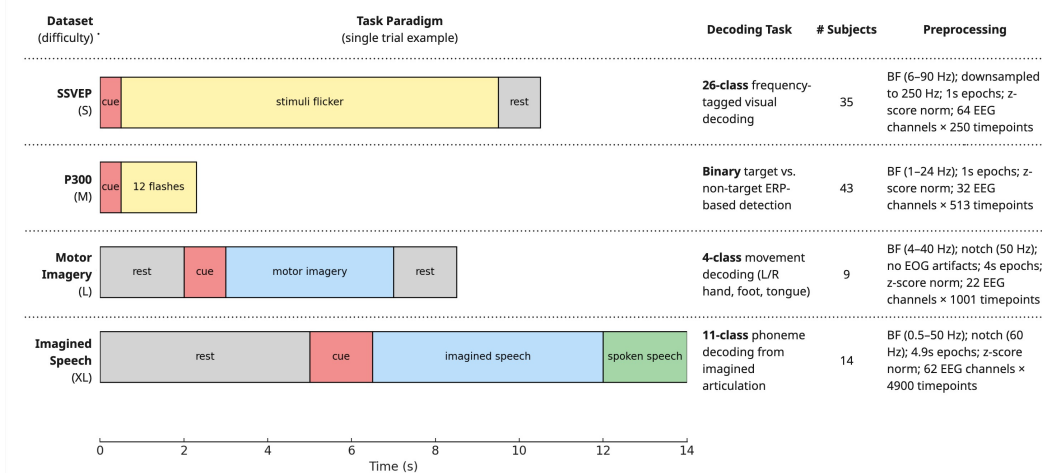
Figure 2: Overview of four EEG datasets ranked by task difficulty from easiest (top) to hardest (bottom). Task paradigms and preprocessing details are adapted from the original publications: SSVEP [40], P300 [18], Motor Imagery [36], and Imagined Speech [45].

enables rigorous evaluation of both personalization and generalization, addressing the inconsistent and often unrealistic split practices prevalent in prior EEG research, where models are evaluated on mixed subject data or using computationally expensive LOSO.

4.2 Baselines

We benchmarked our model against a diverse set of carefully selected baselines to ensure robust and fair comparisons. Our selection criteria were twofold: (i) prioritize architectures that are widely used for generalization to unseen subjects or sessions, and (ii) cover the main inductive biases found in EEG decoding, such as spatial filtering, temporal modeling, and attention mechanisms.

Specifically, we include: (1) **EEGNet** [22], a compact depthwise-separable CNN that is widely adopted for cross-subject generalization due to its strong accuracy–efficiency trade-off; (2) **ShallowFBCSPNet** [32], which implements learnable filter-bank Common Spatial Patterns (CSP) to extract frequency–spatial features; (3) **TIDNet** [19], which introduces dilated convolutions and residual connections to improve robustness under subject shift; (4) **EEGConformer** [33], which combines a convolutional front-end with self-attention to model both local spatial structure and global temporal context; and (5) **EEGTCNet** [15], a temporal convolutional network tailored for EEG that emphasizes causal and dilated temporal modeling, offering complementary inductive bias to purely spatial–spectral models.

All models are evaluated using identical input windows of shape (C, T), and trained with a unified global training schedule to ensure comparability. Public implementations and recommended hyperparameters are used where available, with no method-specific tuning.

4.3 Generalization performance

MultiDiffNet helps with generalization. Unlike raw EEG representations, where class boundaries blur due to subject-specific noise, our learned latent space forms clearly separable, label-aligned clusters (Figure 3). This structured representation enables robust decoding across subjects. As shown in Table 1, *MultiDiffNet* consistently reduces the seen–unseen accuracy gap across all tasks. In SSVEP, it lifts cross-subject accuracy from 81.08% (EEGNet baseline) to 84.72%, further boosted to 85.25% with Temporal Masked Mixup. For comparison, other representative architectures such as ShallowFBCSPNet (58.87%), EEGConformer (51.92%), TIDNet (25.96%), and EEGTCNet (49.57%) fall well behind, highlighting the robustness of our latent-space design.

Even in the low-SNR regime of Imagined Speech, *MultiDiffNet* improves cross-subject accuracy from 10.61% (EEGNet) to 12.12%, while simultaneously achieving a much larger gain on seen-

(A) Latent space evolution across epochs via t-SNE and class centroid distances, showing how the model learns to better separate different classes over time (SSVEP task).

(A.1) Test seen subjects

(A.2) Test unseen subjects
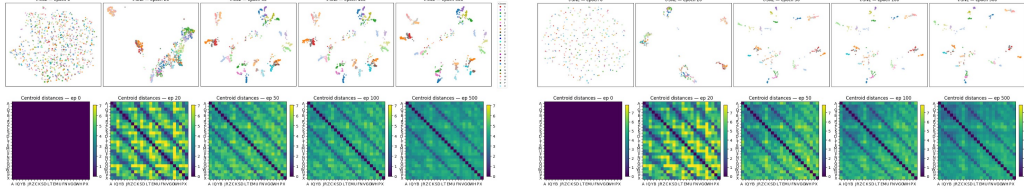
(B) Classification performance from frozen latent space across epochs via accuracy and macro-AUROC on seen/unseen test sets, showing improved generalization over time.

(B.1) SSVEP task

(B.2) P300 task

(B.3) Motor imagery task

(B.4) Imagined speech task
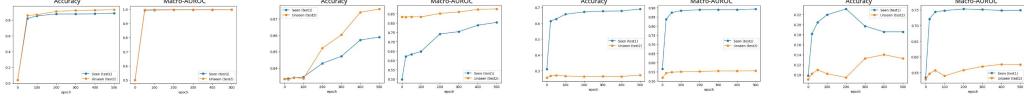
Figure 3: (A) Visualization of latent space across training epochs. (B) Downstream classification performance from frozen latent representations.

subject accuracy (11.26% → 17.57%). Other baselines such as ShallowFBCSPNet (10.48/13.78%), EEGConformer (9.21/10.62%), TIDNet (10.35/9.10%), and EEGTCNet (10.10/12.64%) hover close to chance level on both splits, further highlighting the robustness of our approach. For such a challenging task, even modest absolute gains are meaningful, as they can indicate more reliable signal extraction under extreme noise conditions. On Motor Imagery, *MultiDiffNet* also surpasses most baselines on unseen accuracy, e.g., outperforming TIDNet (34.42%) and EEGTCNet (32.99%), while maintaining competitive seen accuracy (57.69% vs. 44.27% for TIDNet and 58.85% for EEGTCNet). Although it remains slightly below EEGNet (46.18/67.01%), this is likely due to ceiling effects and dataset scale.

4.4 Ablation studies

To understand what drives generalization in *MultiDiffNet*, we ran extensive ablation experiments, over 100 controlled configs. All results are reported for both seen- and unseen-subject accuracy, with statistical evidence matrices and trend-level effect sizes in the Appendix.

Decoder input. Feeding only z to the decoder often matches or exceeds more complex fusion variants. For example, SSVEP unseen accuracy reaches 84.72% with z alone, further boosted to 85.25% with mixup, while more elaborate fusions ($z + x$, $x_{hat}+$ skips) show no consistent gains. These findings validate our architectural decision to decode primarily from z. For completeness, the best accuracies achieved in this ablation are 85.86/84.72 on SSVEP, 85.88/81.41 on P300, 56.89/40.36 on Motor Imagery, and 18.58/12.88 on Imagined Speech (seen/unseen).

Classifier head. A lightweight FC head on z delivers state-of-the-art generalization with minimal complexity. It rivals or outperforms EEGNet classifiers trained on x, especially in low-SNR tasks. This supports our choice to use FC as the default classification head. For completeness, the best accuracies achieved in this ablation are 85.08/84.72 on SSVEP, 85.35/84.12 on P300, 55.85/39.24 on Motor Imagery, and 17.95/11.61 on Imagined Speech (seen/unseen).

Encoder and decoder. Using raw x as encoder input consistently outperforms $\hat{x}$, showing that denoising is useful for regularization. Interestingly, removing the decoder entirely sometimes improves generalization, suggesting that reconstruction may introduce noise if overemphasized. For completeness, the best accuracies in this ablation are 90.95/85.58 on SSVEP, 85.71/80.93 on P300, 55.85/40.16 on Motor Imagery, and 19.22/13.76 on Imagined Speech (seen/unseen).

Loss combinations. Combining CE with mild MSE or contrastive losses improves stability, particularly when auxiliary weights are gently annealed. The best results use $\beta = 0.05$, $\gamma = 0.2$—balancing reconstruction as a regularizer without overpowering the classification objective. For completeness, the best accuracies in this ablation are 86.40/85.58 on SSVEP, 85.69/80.18 on P300, 59.67/41.44 on Motor Imagery, and 19.60/13.51 on Imagined Speech (seen/unseen).

Table 1: Final results across tasks and models. Accuracy is reported for both seen-subject (intra-subject) and unseen-subject (cross-subject) test splits. Tasks are ranked by task difficulty. *Stars denote win percentage:* *** $\geq$ 80%, ** $\geq$ 60%, * $\geq$ 40%. Detailed results are in the Appendix.

Task	Model	Subj.	Classes	Seen Acc. (%)	Unseen Acc. (%)
SSVEP	ShallowFBCSPNet	35	26	$69.58 \pm 1.30^{*}$	$58.87 \pm 9.37^{*}$
	EEGConformer	35	26	66.98 ± 2.83	51.92 ± 9.06
	TIDNet	35	26	28.01 ± 4.12	25.96 ± 5.29
	EEGTCNet	35	26	58.31 ± 4.02	49.57 ± 9.14
	EEGNet	35	26	$89.16 \pm 0.57^{***}$	$81.08 \pm 9.16^{**}$
	MultiDiffNet	35	26	$85.08 \pm 1.53^{**}$	$\mathbf{84.72 \pm 6.03}^{***}$
	MultiDiffNet + Mixup	35	26	$86.79 \pm 1.75^{***}$	$\mathbf{85.25 \pm 6.94}^{***}$
P300	ShallowFBCSPNet	43	2	87.72 ± 0.33	86.20 ± 1.45
	EEGConformer	43	2	$88.54 \pm 0.54^{**}$	86.30 ± 1.73
	TIDNet	43	2	$88.24 \pm 0.31^{*}$	$85.63 \pm 0.58^{**}$
	EEGTCNet	43	2	$88.69 \pm 0.59^{***}$	$87.02 \pm 1.62^{***}$
	EEGNet	43	2	$88.79 \pm 0.67^{***}$	$87.24 \pm 2.01^{***}$
	MultiDiffNet	43	2	85.35 ± 1.12	$79.47 \pm 0.54^{*}$
	MultiDiffNet + Mixup	43	2	85.61 ± 0.52	79.56 ± 4.43
MI	ShallowFBCSPNet	9	4	$64.34 \pm 3.61^{***}$	36.46 ± 6.60
	EEGConformer	9	4	$59.57 \pm 5.60^{**}$	36.49 ± 7.72
	TIDNet	9	4	44.27 ± 2.60	34.42 ± 3.60
	EEGTCNet	9	4	58.85 ± 4.54	32.99 ± 6.94
	EEGNet	9	4	$67.01 \pm 5.38^{***}$	$46.18 \pm 7.20^{***}$
	MultiDiffNet	9	4	55.85 ± 2.80	$39.24 \pm 8.00^{***}$
	MultiDiffNet + Mixup	9	4	$57.69 \pm 3.27^{*}$	36.78 ± 5.23
Img. Speech	ShallowFBCSPNet	14	11	$13.78 \pm 1.55^{**}$	10.48 ± 0.64
	EEGConformer	14	11	10.62 ± 0.82	9.21 ± 3.00
	TIDNet	14	11	9.10 ± 0.54	10.35 ± 0.18
	EEGTCNet	14	11	12.64 ± 1.58	10.10 ± 0.64
	EEGNet	14	11	$11.26 \pm 2.01^{*}$	$10.61 \pm 0.93^{*}$
	MultiDiffNet	14	11	$\mathbf{15.55 \pm 0.62}^{***}$	$\mathbf{11.62 \pm 1.29}^{***}$
	MultiDiffNet + Mixup	14	11	$\mathbf{17.57 \pm 1.16}^{***}$	$\mathbf{12.12 \pm 0.38}^{***}$

Mixup strategies. Mixup effects are task-specific. For SSVEP, *Temporal Masked Mixup* outperforms all variants. Motor Imagery benefits from *Weighted Average Mixup*, while P300 and Imagined Speech show limited sensitivity, highlighting that mixup is most impactful in high-SNR regimes. For completeness, the best accuracies in this ablation are 87.84/85.26 on SSVEP, 85.78/79.56 on P300, 63.44/38.83 on Motor Imagery, and 19.47/12.12 on Imagined Speech (seen/unseen).

5 Conclusions and future work

We presented *MultiDiffNet*, a diffusion-based neural decoder that learns a compact, multi-objective latent space for EEG decoding without synthetic augmentation. Through unified benchmarks and rigorous cross-subject evaluation, we showed that *MultiDiffNet* achieves strong generalization across diverse BCI paradigms, particularly in challenging low-signal settings such as SSVEP and Imagined Speech. Our statistical analysis framework further addresses reproducibility challenges in low-trial EEG research. Future work will explore scaling *MultiDiffNet* to larger and more diverse EEG datasets and extending the architecture to other neural modalities.

Acknowledgments

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Appendix

Appendix overview

This appendix provides full experimental details, supporting results, and statistical analyses that complement the main paper:

- **Section A: Implementation and experimental details**
  Covers architecture choices, training setups, loss function derivations, and augmentation strategies.

- **Section B: Generalization performance and analysis**
  Presents extended decoding results across all tasks with seen/unseen splits.

- **Section C: Complete ablation studies**
  Contains exhaustive ablations over decoder input types, classifier heads, architectural variants, mixup strategies, and loss function choices. Each is accompanied by multi-task results.

- **Section D: Complete statistical reporting results**
  Details our trend-level statistical framework, including effect size estimation, Bayesian comparison, and win-rate matrix construction.

We include additional sections from the main text (e.g., Related Work) that were moved here due to space constraints.

A Implementation and experimental details

A.1 Loss functions

Classification loss.

We use either cross-entropy (CE) or mean squared error (MSE).

CE uses softmax over the classifier logits:

$$\mathcal{L}_{\text{CE}} = -\sum_{c=1}^{N} y_c \log \hat{y}_c, \quad \hat{y} = \text{Softmax}(\text{FC}(z))$$

MSE treats classification as regression:

$$\mathcal{L}_{\text{MSE}} = \|\hat{y} - y\|_2^2$$

Supervised contrastive loss.

A projection head maps the normalized embedding z to z_{proj}. We then use the SupCon loss:

$$\mathcal{L}_{\text{SupCon}} = \sum_{i \in I} \frac{-1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp(z_i \cdot z_p / \tau)}{\sum_{a \in A(i)} \exp(z_i \cdot z_a / \tau)}$$

where τ is the temperature, $P(i)$ are positives, and $A(i)$ includes all non-anchor samples.

L1 reconstruction loss.

The decoder learns to reconstruct the DDPM-denoised signal:

$$\mathcal{L}_{\text{L1}} = \|x_{\text{dec}} - \hat{x}\|_1$$

We also compute an auxiliary loss $\|\hat{x} - x\|_1$ to guide DDPM training but exclude it from the final objective.

B Generalization performance and analysis

Task Paradigm	Configuration	Seen				Unseen			
		Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
SSVEP	EEGNet	89.16 ± 0.57	89.16 ± 0.55	89.16 ± 0.57	99.72 ± 0.04	81.09 ± 9.16	81.58 ± 8.21	81.09 ± 9.16	98.75 ± 1.35
	MultiDiffNet	85.08 ± 1.53	84.95 ± 1.66	85.08 ± 1.53	99.37 ± 0.05	$\mathbf{84.72 \pm 6.04}$	$\mathbf{84.44 \pm 6.21}$	$\mathbf{84.72 \pm 6.04}$	$\mathbf{98.90 \pm 0.76}$
	MultiDiffNet + Temp. Masked Mixup	86.79 ± 1.75	86.00 ± 0.00	86.00 ± 0.00	99.00 ± 0.00	85.26 ± 6.94	83.00 ± 0.07	83.00 ± 0.07	99.00 ± 0.01
P300	EEGNet	88.79 ± 0.68	78.09 ± 1.73	76.03 ± 1.99	89.43 ± 1.06	87.24 ± 2.01	73.72 ± 5.30	71.40 ± 5.69	85.97 ± 4.19
	MultiDiffNet	85.24 ± 1.02	63.06 ± 5.33	60.79 ± 4.04	77.54 ± 4.84	76.26 ± 3.61	62.80 ± 3.19	64.95 ± 2.86	71.71 ± 4.68
MI	EEGNet	64.09 ± 5.77	63.62 ± 5.79	64.09 ± 5.77	87.09 ± 3.11	43.89 ± 8.33	42.57 ± 8.35	43.89 ± 8.33	71.95 ± 7.51
	MultiDiffNet	59.03 ± 6.73	57.12 ± 7.83	59.03 ± 6.73	83.05 ± 2.97	40.25 ± 4.63	38.82 ± 4.72	40.25 ± 4.63	68.06 ± 4.98
Imag. Speech	EEGNet	11.26 ± 2.01	11.19 ± 1.98	11.26 ± 2.02	52.02 ± 0.42	10.61 ± 0.93	10.17 ± 0.75	10.61 ± 0.93	50.33 ± 1.25
	MultiDiffNet	$\mathbf{15.55 \pm 0.62}$	9.61 ± 1.23	$\mathbf{15.53 \pm 0.62}$	$\mathbf{71.24 \pm 1.66}$	$\mathbf{11.62 \pm 1.29}$	7.84 ± 1.32	$\mathbf{11.62 \pm 1.29}$	$\mathbf{57.15 \pm 3.18}$

Table 2: Final results across tasks and models. Accuracy (mean ± std) reported separately for both seen-subject (intra-subject) and unseen-subject (cross-subject) test splits. Tasks are ranked by task difficulty.

C Complete ablation studies

C.1 Decoder input ablations

Decoder Input	SSVEP		P300		Motor Imagery		Imagined Speech	
	Seen	Unseen	Seen	Unseen	Seen	Unseen	Seen	Unseen
x + x_hat + skips	**85.86 ± 0.38**	83.12 ± 6.90	85.07 ± 1.03	79.15 ± 3.73	53.08 ± 4.68	38.74 ± 6.58	17.07 ± 1.86	12.37 ± 2.79
x + x_hat	85.16 ± 0.95	84.40 ± 6.22	85.62 ± 0.43	78.59 ± 1.56	54.56 ± 1.83	40.13 ± 8.25	**18.58 ± 2.13**	10.48 ± 2.87
x + skips	85.63 ± 0.29	81.73 ± 7.29	85.75 ± 0.09	77.93 ± 1.43	54.66 ± 2.58	**40.36 ± 7.30**	17.32 ± 1.40	11.74 ± 2.42
x_hat + skips	85.70 ± 0.14	83.55 ± 7.93	85.60 ± 0.57	**81.41 ± 0.98**	54.27 ± 2.88	40.31 ± 7.48	17.19 ± 0.47	12.50 ± 1.72
skips only	84.03 ± 1.33	82.59 ± 4.69	84.53 ± 0.82	75.52 ± 4.93	53.77 ± 2.80	37.33 ± 6.58	17.70 ± 2.30	11.11 ± 2.24
z only	85.08 ± 1.53	**84.72 ± 6.04**	85.35 ± 1.12	79.47 ± 0.54	55.85 ± 2.80	39.24 ± 7.95	15.55 ± 0.62	11.62 ± 1.29
z + x	84.89 ± 0.55	82.05 ± 6.57	85.42 ± 0.09	79.07 ± 3.97	**56.89 ± 2.92**	40.02 ± 7.01	18.08 ± 1.74	10.86 ± 2.81
z + x_hat	85.16 ± 0.22	82.59 ± 8.17	**85.88 ± 0.38**	79.47 ± 0.64	55.61 ± 3.04	39.64 ± 6.02	17.57 ± 0.37	**12.88 ± 1.07**
z + skips	85.31 ± 0.59	83.55 ± 5.60	85.79 ± 0.66	79.09 ± 5.66	52.08 ± 3.04	37.01 ± 5.67	17.83 ± 1.09	10.23 ± 1.93

Table 3: Ablation study of decoder input combinations for *MultiDiffNet*. Accuracy (mean ± std) reported separately for seen- and unseen-subject test splits across four tasks.

Configuration	SSVEP (Seen)				SSVEP (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
x + x_hat + skips	**85.86 ± 0.38**	**85.84 ± 0.40**	**85.86 ± 0.38**	**99.50 ± 0.03**	83.12 ± 6.91	82.85 ± 6.92	83.12 ± 6.91	98.79 ± 0.94
x + x_hat	85.16 ± 0.95	85.14 ± 0.96	85.16 ± 0.95	99.40 ± 0.06	84.40 ± 6.22	84.14 ± 6.36	84.40 ± 6.22	**98.94 ± 0.80**
x_hat + skips	85.70 ± 0.15	85.67 ± 0.14	85.70 ± 0.15	99.45 ± 0.01	83.55 ± 7.93	83.33 ± 8.13	83.55 ± 7.93	98.92 ± 0.84
x + skips	85.63 ± 0.29	85.61 ± 0.32	85.63 ± 0.29	99.40 ± 0.03	81.73 ± 7.29	81.52 ± 7.44	81.73 ± 7.29	98.85 ± 0.95
skips	84.03 ± 1.33	83.86 ± 1.46	84.03 ± 1.33	99.41 ± 0.02	82.59 ± 4.69	82.22 ± 4.66	82.59 ± 4.69	98.80 ± 0.91
z only	85.08 ± 1.53	84.95 ± 1.66	85.08 ± 1.53	99.37 ± 0.05	**84.72 ± 6.04**	**84.44 ± 6.21**	**84.72 ± 6.04**	98.90 ± 0.76
z + x	84.89 ± 0.55	84.88 ± 0.63	84.89 ± 0.55	99.45 ± 0.08	82.05 ± 6.57	81.93 ± 6.55	82.05 ± 6.57	98.81 ± 0.87
z + x_hat	85.16 ± 0.22	85.12 ± 0.15	85.16 ± 0.22	99.45 ± 0.07	82.59 ± 8.17	82.39 ± 8.37	82.59 ± 8.17	98.69 ± 0.95
z + skips	85.31 ± 0.59	85.28 ± 0.64	85.31 ± 0.59	99.48 ± 0.03	83.55 ± 5.60	83.10 ± 5.65	83.55 ± 5.60	98.82 ± 0.82

Table 4: Ablation study of decoder input combinations for *MultiDiffNet* in the ssvep task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks.

Configuration	P300 (Seen)				P300 (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
x + x_hat + skips	85.07 ± 1.03	**67.21 ± 1.80**	**64.55 ± 1.39**	77.87 ± 2.81	79.15 ± 3.73	63.75 ± 4.99	64.99 ± 6.27	71.06 ± 7.65
x + x_hat	85.62 ± 0.43	64.19 ± 2.47	61.38 ± 1.99	77.86 ± 2.52	78.59 ± 1.56	63.56 ± 3.74	64.68 ± 4.86	71.54 ± 5.86
x_hat + skips	85.60 ± 0.57	65.95 ± 1.10	63.00 ± 1.28	**79.70 ± 0.77**	**81.41 ± 0.98**	64.91 ± 4.68	64.99 ± 6.23	**72.75 ± 7.16**
x + skips	85.75 ± 0.09	65.96 ± 0.60	62.87 ± 0.57	79.66 ± 1.29	77.93 ± 1.43	62.76 ± 1.61	64.23 ± 3.87	70.32 ± 2.97
skips	84.53 ± 0.82	65.14 ± 0.95	62.79 ± 1.48	77.33 ± 1.39	75.52 ± 4.93	62.34 ± 4.91	64.58 ± 4.17	69.91 ± 6.11
z only	85.35 ± 1.12	64.39 ± 4.95	61.88 ± 4.10	77.14 ± 4.35	79.47 ± 0.54	63.67 ± 1.58	63.95 ± 1.86	70.79 ± 3.27
z + x	85.42 ± 0.09	62.70 ± 1.63	60.17 ± 1.34	75.48 ± 2.57	79.07 ± 3.97	63.93 ± 5.15	64.33 ± 4.48	70.53 ± 5.68
z + x_hat	**85.88 ± 0.38**	63.44 ± 1.79	60.60 ± 1.37	76.94 ± 3.20	79.47 ± 0.64	**65.01 ± 3.74**	**66.48 ± 5.47**	72.36 ± 5.08
z + skips	85.79 ± 0.66	65.02 ± 2.72	62.05 ± 2.19	78.77 ± 2.18	79.09 ± 5.66	64.69 ± 5.87	65.70 ± 5.82	71.68 ± 7.35

Table 5: Ablation study of decoder input combinations for *MultiDiffNet* in the P300 task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks.

Configuration	MI (Seen)				MI (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
x + x_hat + skips	53.08 ± 4.68	48.79 ± 5.69	53.08 ± 4.68	80.78 ± 4.91	38.74 ± 6.58	37.74 ± 6.87	38.74 ± 6.58	65.41 ± 6.77
x + x_hat	54.56 ± 1.83	52.83 ± 1.61	54.56 ± 1.83	83.00 ± 0.71	40.13 ± 8.25	38.69 ± 8.47	40.13 ± 8.25	66.58 ± 6.26
x_hat + skips	54.27 ± 2.88	52.66 ± 4.08	54.27 ± 2.88	81.45 ± 1.68	40.31 ± 7.48	39.13 ± 7.91	40.31 ± 7.48	66.60 ± 6.85
x + skips	54.66 ± 2.58	52.09 ± 4.13	54.66 ± 2.58	82.00 ± 1.47	**40.36 ± 7.30**	39.25 ± 7.58	**40.36 ± 7.30**	66.33 ± 6.98
skips	53.77 ± 2.80	51.12 ± 3.68	53.77 ± 2.80	**83.80 ± 1.37**	37.33 ± 6.58	36.21 ± 7.14	37.33 ± 6.58	63.85 ± 5.14
z only	55.85 ± 2.80	54.25 ± 3.15	55.85 ± 2.80	82.72 ± 0.86	39.24 ± 7.95	38.07 ± 7.86	39.24 ± 7.95	**66.70 ± 7.32**
z + x	**56.89 ± 2.92**	**54.60 ± 4.39**	**56.89 ± 2.92**	83.41 ± 1.95	40.02 ± 7.01	**39.41 ± 7.09**	40.02 ± 7.01	65.69 ± 6.78
z + x_hat	55.61 ± 3.04	53.07 ± 4.23	55.61 ± 3.04	82.65 ± 1.04	39.64 ± 6.02	38.78 ± 5.78	39.64 ± 6.02	65.44 ± 5.60
z + skips	52.08 ± 3.04	47.78 ± 3.57	52.08 ± 3.04	82.62 ± 1.66	37.01 ± 5.67	35.56 ± 6.21	37.01 ± 5.67	64.71 ± 6.48

Table 6: Ablation study of decoder input combinations for *MultiDiffNet* in the MI task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks.

Configuration	Imag. Speech (Seen)				Imag. Speech (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
x + x_hat + skips	17.07 ± 1.86	13.35 ± 2.60	17.05 ± 1.86	71.15 ± 3.16	12.37 ± 2.79	9.76 ± 2.17	12.37 ± 2.79	57.98 ± 4.50
x + x_hat	**18.58 ± 2.13**	13.39 ± 2.72	**18.56 ± 2.14**	72.58 ± 1.68	10.48 ± 2.87	7.63 ± 0.81	10.48 ± 2.87	56.64 ± 6.04
x_hat + skips	17.19 ± 0.47	12.90 ± 1.56	17.17 ± 0.47	**73.16 ± 0.59**	12.50 ± 1.72	9.02 ± 0.18	12.50 ± 1.72	56.86 ± 4.74
x + skips	17.32 ± 1.40	13.92 ± 1.93	17.30 ± 1.39	71.93 ± 2.02	11.74 ± 2.42	8.57 ± 1.97	11.74 ± 2.42	56.47 ± 3.87
skips	17.70 ± 2.30	12.91 ± 2.52	17.68 ± 2.32	72.61 ± 1.56	11.11 ± 2.24	9.59 ± 2.13	11.11 ± 2.24	56.24 ± 2.03
z only	15.55 ± 0.62	9.61 ± 1.23	15.53 ± 0.62	71.24 ± 1.66	11.62 ± 1.29	7.84 ± 1.32	11.62 ± 1.29	57.15 ± 3.18
z + x	18.08 ± 1.74	**14.40 ± 1.08**	18.06 ± 1.76	73.08 ± 0.57	10.86 ± 2.81	8.50 ± 1.39	10.86 ± 2.81	55.71 ± 3.62
z + x_hat	17.57 ± 0.37	11.16 ± 0.56	17.56 ± 0.37	72.45 ± 1.27	**12.88 ± 1.07**	**8.16 ± 0.48**	**12.88 ± 1.07**	**58.78 ± 1.31**
z + skips	17.83 ± 1.09	13.25 ± 1.09	17.80 ± 1.07	72.86 ± 0.78	10.23 ± 1.93	7.72 ± 0.59	10.23 ± 1.93	55.81 ± 4.16

Table 7: Ablation study of decoder input combinations for *MultiDiffNet* in the imagined speech task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks.

C.2 Classifier head ablations

Classifier Variant	SSVEP		P300		Motor Imagery		Imagined Speech	
	Seen	Unseen	Seen	Unseen	Seen	Unseen	Seen	Unseen
x → EEGNet	**89.16 ± 0.57**	**81.09 ± 9.16**	**88.79 ± 0.68**	**87.24 ± 2.01**	**67.01 ± 5.38**	**46.18 ± 7.21**	11.26 ± 2.01	10.61 ± 0.93
x_hat → EEGNet	10.61 ± 4.96	9.19 ± 7.57	79.18 ± 1.32	79.08 ± 1.49	26.63 ± 0.21	25.84 ± 0.43	9.86 ± 3.27	7.70 ± 1.09
deco_out → EEGNet	80.22 ± 0.99	70.62 ± 6.38	84.29 ± 0.77	83.52 ± 1.07	52.63 ± 3.56	35.16 ± 5.48	**16.94 ± 1.28**	**10.73 ± 1.59**
x → FC	10.72 ± 2.01	11.43 ± 5.31	83.30 ± 0.05	83.33 ± 0.00	47.12 ± 0.92	29.48 ± 2.58	16.94 ± 1.97	8.71 ± 0.93
x_hat → FC	3.73 ± 0.25	4.06 ± 0.54	83.33 ± 0.00	83.33 ± 0.00	25.30 ± 0.42	24.77 ± 0.33	10.62 ± 0.02	8.96 ± 0.94
deco_out → FC	77.62 ± 1.44	69.55 ± 6.77	85.10 ± 0.35	84.11 ± 1.01	50.64 ± 2.08	33.74 ± 4.12	17.95 ± 1.39	8.71 ± 1.07
z → FC	85.08 ± 1.53	84.72 ± 6.04	85.35 ± 0.35	84.12 ± 1.01	55.85 ± 2.80	39.24 ± 7.95	15.55 ± 0.62	**11.61 ± 1.29**

Table 8: Ablation study of classifier variants. Accuracy (mean ± std) reported separately for seen- and unseen-subject test splits across four tasks.

Configuration	SSVEP (Seen)				SSVEP (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
eegn_clsf_x	**89.16 ± 0.57**	**89.16 ± 0.55**	**89.16 ± 0.57**	**99.72 ± 0.04**	81.09 ± 9.16	81.58 ± 8.21	81.09 ± 9.16	98.75 ± 1.35
eegn_clsf_x_hat	10.61 ± 4.96	8.73 ± 4.32	10.61 ± 4.96	59.86 ± 5.14	9.19 ± 7.57	8.15 ± 6.91	9.19 ± 7.57	59.39 ± 8.07
eegn_clsf_deco_out	80.23 ± 0.99	80.19 ± 1.01	80.23 ± 0.99	99.35 ± 0.03	70.62 ± 6.38	69.69 ± 6.48	70.62 ± 6.38	98.21 ± 1.26
fc_clsf_x	10.72 ± 2.01	8.91 ± 1.93	10.72 ± 2.01	73.43 ± 3.35	11.43 ± 5.31	9.63 ± 5.44	11.43 ± 5.31	70.57 ± 5.03
fc_clsf_x_hat	3.73 ± 0.25	0.68 ± 0.30	3.73 ± 0.25	49.74 ± 0.48	4.06 ± 0.54	1.17 ± 0.32	4.06 ± 0.54	49.43 ± 1.77
fc_clsf_deco_out	77.62 ± 1.44	77.49 ± 1.59	77.62 ± 1.44	99.25 ± 0.06	69.55 ± 6.77	69.56 ± 6.81	69.55 ± 6.77	98.03 ± 1.17
fc_clsf_z	85.08 ± 1.53	84.95 ± 1.66	85.08 ± 1.53	99.37 ± 0.05	**84.72 ± 6.04**	**84.44 ± 6.21**	**84.72 ± 6.04**	**98.90 ± 0.76**

Table 9: Ablation study of `classifier_variant` and `classifier_input` combinations on the SSVEP task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on both seen- and unseen-subject test splits. Results are averaged across four tasks ("eegn" = EEGNet, "clsf" = classifier, "deco" = decoder).

Configuration	P300 (Seen)				P300 (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
eegn_clsf_x	**88.79 ± 0.68**	**78.09 ± 1.73**	**76.03 ± 1.99**	**89.43 ± 1.06**	**87.24 ± 2.01**	**73.72 ± 5.30**	**71.40 ± 5.69**	**85.97 ± 4.19**
eegn_clsf_x_hat	79.18 ± 1.32	48.09 ± 2.56	49.70 ± 1.82	46.94 ± 8.58	79.08 ± 1.49	47.72 ± 1.89	49.41 ± 1.50	45.95 ± 6.80
eegn_clsf_deco_out	84.29 ± 0.77	56.01 ± 7.51	56.08 ± 4.34	66.90 ± 12.00	83.52 ± 1.07	54.02 ± 8.11	54.95 ± 5.26	64.43 ± 9.42
fc_clsf_x	83.30 ± 0.05	45.50 ± 0.06	50.00 ± 0.00	50.08 ± 0.23	83.33 ± 0.00	45.45 ± 0.00	50.00 ± 0.00	50.32 ± 0.38
fc_clsf_x_hat	83.33 ± 0.00	45.45 ± 0.00	50.00 ± 0.00	49.85 ± 0.50	83.33 ± 0.00	45.45 ± 0.00	50.00 ± 0.00	50.31 ± 0.30
fc_clsf_deco_out	85.10 ± 0.35	60.43 ± 2.05	58.48 ± 1.48	74.88 ± 2.73	84.12 ± 1.01	56.01 ± 5.84	55.80 ± 3.95	70.24 ± 6.64
fc_clsf_z	85.35 ± 1.12	64.39 ± 4.95	61.88 ± 4.10	77.14 ± 4.35	79.47 ± 0.54	63.67 ± 1.58	63.95 ± 1.86	70.79 ± 3.27

Table 10: Ablation study of `classifier_variant`, and `classifier_input` combinations in the P300 task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("eegn" = EEGNet, "clsf" = classifier, "deco" = decoder).

Configuration	MI (Seen)				MI (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
eegn_clsf_x	**67.01 ± 5.38**	**67.01 ± 5.39**	**67.01 ± 5.38**	**88.66 ± 3.28**	**46.18 ± 7.21**	**45.69 ± 7.30**	**46.18 ± 7.21**	**72.75 ± 5.62**
eegn_clsf_x_hat	26.64 ± 0.21	20.09 ± 3.08	26.64 ± 0.21	53.43 ± 1.52	25.84 ± 0.43	18.80 ± 4.43	25.84 ± 0.43	50.57 ± 0.75
eegn_clsf_deco_out	52.63 ± 3.56	51.30 ± 3.43	52.63 ± 3.56	79.26 ± 2.99	35.16 ± 5.48	31.97 ± 4.78	35.16 ± 5.48	60.71 ± 5.32
fc_clsf_x	47.12 ± 0.92	46.83 ± 1.08	47.12 ± 0.92	73.82 ± 0.72	29.48 ± 2.59	26.58 ± 2.96	29.48 ± 2.59	57.16 ± 3.26
fc_clsf_x_hat	25.30 ± 0.42	12.15 ± 3.04	25.30 ± 0.42	50.92 ± 1.51	24.77 ± 0.33	11.37 ± 1.93	24.77 ± 0.33	49.21 ± 1.85
fc_clsf_deco_out	50.64 ± 2.08	49.99 ± 2.38	50.64 ± 2.08	76.84 ± 2.48	33.74 ± 4.12	30.64 ± 5.43	33.74 ± 4.12	60.94 ± 4.40
fc_clsf_z	55.85 ± 2.80	54.25 ± 3.15	55.85 ± 2.80	82.72 ± 0.86	39.24 ± 7.95	38.07 ± 7.86	39.24 ± 7.95	66.70 ± 7.32

Table 11: Ablation study of `classifier_variant`, and `classifier_input` combinations in the MI task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("eegn" = EEGNet, "clsf" = classifier, "deco" = decoder).

Configuration	Imag. Speech (Seen)				Imag. Speech (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
eegn_clsf_x	11.26 ± 2.01	11.19 ± 1.98	11.26 ± 2.02	52.02 ± 0.42	10.61 ± 0.93	**10.17 ± 0.75**	10.61 ± 0.93	50.33 ± 1.25
eegn_clsf_x_hat	9.86 ± 3.27	8.82 ± 2.53	9.85 ± 3.27	50.06 ± 1.59	7.70 ± 1.09	6.15 ± 0.85	7.70 ± 1.09	49.10 ± 3.36
eegn_clsf_deco_out	**16.94 ± 1.28**	**14.73 ± 0.81**	**16.92 ± 1.26**	**73.33 ± 0.13**	10.73 ± 1.59	6.33 ± 1.77	10.73 ± 1.59	51.50 ± 1.99
fc_clsf_x	16.94 ± 1.97	16.68 ± 1.78	16.93 ± 1.98	68.36 ± 0.93	8.71 ± 0.93	6.31 ± 0.76	8.71 ± 0.93	50.99 ± 0.69
fc_clsf_x_hat	10.62 ± 0.02	4.48 ± 1.18	10.61 ± 0.00	51.62 ± 1.79	8.96 ± 0.94	3.48 ± 0.57	8.96 ± 0.94	51.20 ± 0.41
fc_clsf_deco_out	17.95 ± 1.39	17.02 ± 1.18	17.95 ± 1.39	74.32 ± 0.97	8.71 ± 1.07	4.46 ± 0.35	8.71 ± 1.07	49.30 ± 1.62
fc_clsf_z	15.55 ± 0.62	9.61 ± 1.23	15.53 ± 0.62	71.24 ± 1.66	**11.62 ± 1.29**	7.84 ± 1.32	**11.62 ± 1.29**	**57.15 ± 3.18**

Table 12: Ablation study of `classifier_variant`, and `classifier_input` combinations in the imagened speech task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks.

C.3 Encoder and decoder ablations

Configuration	SSVEP		P300		Motor Imagery		Imagained Speech	
	Seen	Unseen	Seen	Unseen	Seen	Unseen	Seen	Unseen
u_dp-x-u_deco	85.08 ± 1.53	84.72 ± 6.04	85.35 ± 1.12	79.47 ± 0.54	$\mathbf{55.85 \pm 2.80}$	39.24 ± 7.95	15.55 ± 0.62	11.62 ± 1.29
u_dp-x-n_deco	85.51 ± 0.63	83.55 ± 5.60	$\mathbf{85.71 \pm 0.38}$	$\mathbf{80.93 \pm 1.52}$	53.22 ± 4.58	$\mathbf{40.16 \pm 6.17}$	18.71 ± 1.43	10.98 ± 1.61
u_dp-x_h-u_deco	6.53 ± 1.07	7.58 ± 2.35	80.02 ± 4.40	69.43 ± 4.04	25.20 ± 0.86	26.04 ± 0.07	8.85 ± 0.37	9.47 ± 1.35
u_dp-x_h-n_deco	6.72 ± 1.35	7.05 ± 1.63	83.11 ± 0.18	66.39 ± 6.24	28.12 ± 0.99	26.04 ± 0.28	8.97 ± 0.16	8.33 ± 2.75
n_dp-x-u_deco	90.29 ± 0.29	84.94 ± 8.16	85.36 ± 1.28	78.84 ± 5.44	55.06 ± 5.31	36.49 ± 2.70	$\mathbf{19.22 \pm 2.13}$	$\mathbf{13.76 \pm 1.25}$
n_dp-x-n_deco	$\mathbf{90.95 \pm 0.83}$	$\mathbf{85.58 \pm 6.15}$	85.49 ± 0.66	79.46 ± 0.72	53.22 ± 4.44	38.54 ± 3.87	19.22 ± 0.20	11.36 ± 1.93

Table 13: Ablation study of ddpm_variant, encoder_input, and decoder_variant combinations. Accuracy (mean ± std) reported separately for seen/unseen-subject test splits across tasks ("dp" = ddpm_variant, "x_h" = x_hat, "deco" = decoder_variant,"u" = use,"n" = not use,).

Configuration	SSVEP (Seen)				SSVEP (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
u_dp_x_u_deco	85.08 ± 1.53	84.95 ± 1.66	85.08 ± 1.53	99.37 ± 0.05	84.72 ± 6.04	84.44 ± 6.21	84.72 ± 6.04	98.90 ± 0.76
u_dp_x_n_deco	85.51 ± 0.63	85.48 ± 0.69	85.51 ± 0.63	99.44 ± 0.02	83.55 ± 5.60	83.25 ± 6.02	83.55 ± 5.60	98.92 ± 0.99
u_dp_x_h_u_deco	6.53 ± 1.07	4.89 ± 0.91	6.53 ± 1.07	55.27 ± 1.84	7.59 ± 2.35	7.11 ± 2.35	7.59 ± 2.35	56.22 ± 2.99
u_dp_x_h_n_deco	6.72 ± 1.35	4.38 ± 1.43	6.72 ± 1.35	56.19 ± 3.11	7.05 ± 1.63	6.48 ± 1.48	7.05 ± 1.63	54.26 ± 2.37
n_dp_x_u_deco	90.29 ± 0.29	90.36 ± 0.28	90.29 ± 0.29	$\mathbf{99.68 \pm 0.04}$	84.94 ± 8.16	84.53 ± 8.58	84.94 ± 8.16	$\mathbf{99.11 \pm 0.88}$
n_dp_x_n_deco	$\mathbf{90.95 \pm 0.83}$	$\mathbf{91.02 \pm 0.84}$	$\mathbf{90.95 \pm 0.83}$	99.68 ± 0.01	$\mathbf{85.58 \pm 6.15}$	$\mathbf{85.32 \pm 6.37}$	$\mathbf{85.58 \pm 6.15}$	99.07 ± 0.83

Table 14: Ablation study of ddpm_variant, encoder_input and decoder_variant combinations in the SSVEP task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("dp" = ddpm_variant, "x_h" = x_hat, "deco" = decoder_variant,"u" = use,"n" = not use).

Configuration	P300 (Seen)				P300 (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
u_dp_x_u_deco	85.35 ± 1.12	64.39 ± 4.95	61.88 ± 4.10	77.14 ± 4.35	79.47 ± 0.54	63.67 ± 1.58	63.95 ± 1.86	70.79 ± 3.27
u_dp_x_n_deco	$\mathbf{85.71 \pm 0.38}$	67.06 ± 2.38	64.12 ± 2.35	$\mathbf{79.67 \pm 1.76}$	$\mathbf{80.94 \pm 1.53}$	64.74 ± 5.62	65.57 ± 6.99	72.64 ± 7.24
u_dp_x_h_u_deco	80.02 ± 4.40	48.44 ± 3.74	51.30 ± 1.76	52.24 ± 4.16	69.43 ± 4.04	50.33 ± 1.63	50.64 ± 1.36	50.71 ± 2.41
u_dp_x_h_n_deco	83.11 ± 0.18	45.76 ± 0.42	50.02 ± 0.11	48.80 ± 1.49	66.39 ± 6.24	47.84 ± 2.84	48.03 ± 2.67	46.97 ± 3.74
n_dp_x_u_deco	85.36 ± 1.28	$\mathbf{68.45 \pm 3.02}$	$\mathbf{66.09 \pm 3.16}$	79.59 ± 2.08	78.84 ± 5.44	$\mathbf{65.21 \pm 5.06}$	$\mathbf{66.28 \pm 3.31}$	$\mathbf{73.36 \pm 6.13}$
n_dp_x_n_deco	85.50 ± 0.66	62.95 ± 4.25	60.57 ± 3.45	76.39 ± 3.83	79.46 ± 0.72	64.63 ± 2.54	65.53 ± 3.49	72.86 ± 3.49

Table 15: Ablation study of ddpm_variant, encoder_input and decoder_variant combinations in the P300 task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("dp" = ddpm_variant, "x_h" = x_hat, "deco" = decoder_variant,"u" = use,"n" = not use).

Configuration	MI (Seen)				MI (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
u_dp_x_u_deco	**55.85 ± 2.80**	**54.25 ± 3.15**	**55.85 ± 2.80**	**82.72 ± 0.86**	39.24 ± 7.95	**38.07 ± 7.86**	39.24 ± 7.95	**66.70 ± 7.32**
u_dp_x_n_deco	53.22 ± 4.58	51.30 ± 5.58	53.22 ± 4.58	81.97 ± 1.51	40.16 ± 6.18	37.50 ± 4.49	**40.16 ± 6.18**	65.69 ± 6.26
u_dp_x_h_u_deco	25.20 ± 0.86	16.31 ± 1.77	25.20 ± 0.86	51.24 ± 0.50	26.04 ± 0.07	22.09 ± 1.31	26.04 ± 0.07	49.78 ± 0.32
u_dp_x_h_n_deco	28.12 ± 0.99	23.52 ± 3.09	28.12 ± 0.99	52.46 ± 0.57	26.04 ± 0.28	19.57 ± 1.42	26.04 ± 0.28	53.04 ± 2.04
n_dp_x_u_deco	55.06 ± 5.31	52.65 ± 8.20	55.06 ± 5.31	81.31 ± 5.04	36.49 ± 2.70	35.02 ± 2.24	36.49 ± 2.70	62.69 ± 2.92
n_dp_x_n_deco	53.22 ± 4.44	50.50 ± 5.52	53.22 ± 4.44	81.79 ± 1.09	38.54 ± 3.87	36.72 ± 3.79	38.54 ± 3.87	64.42 ± 4.25

Table 16: Ablation study of ddpm_variant, encoder_input and decoder_variant combinations in the MI task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("dp" = ddpm_variant, "x_h" = x_hat, "deco" = decoder_variant,"u" = use,"n" = not use).

Configuration	Imag. Speech (Seen)				Imag. Speech (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
u_dp_x_u_deco	15.55 ± 0.62	9.61 ± 1.23	15.53 ± 0.62	71.24 ± 1.66	11.62 ± 1.29	7.84 ± 1.32	11.62 ± 1.29	57.15 ± 3.18
u_dp_x_n_deco	18.71 ± 1.43	13.92 ± 2.57	18.69 ± 1.46	72.81 ± 0.13	10.98 ± 1.61	8.06 ± 0.55	10.98 ± 1.61	56.99 ± 4.34
u_dp_x_h_use_deco	8.85 ± 0.37	1.72 ± 0.28	8.84 ± 0.36	51.77 ± 1.23	9.47 ± 1.35	7.09 ± 0.63	9.47 ± 1.35	52.19 ± 2.60
u_dp_x_h_n_deco	8.98 ± 0.16	2.22 ± 0.99	8.96 ± 0.18	49.93 ± 0.32	8.33 ± 2.75	6.21 ± 1.83	8.33 ± 2.75	51.19 ± 3.38
n_dp_x_u_deco	**19.22 ± 2.13**	14.48 ± 1.41	**19.20 ± 2.11**	**74.23 ± 1.24**	**13.76 ± 1.25**	**10.59 ± 0.42**	**13.76 ± 1.25**	**57.67 ± 3.22**
n_dp_x_n_deco	19.22 ± 0.20	**14.78 ± 0.77**	19.19 ± 0.18	73.51 ± 1.08	11.36 ± 1.93	7.95 ± 2.65	11.36 ± 1.93	54.54 ± 0.85

Table 17: Ablation study of ddpm_variant, encoder_input and decoder_variant combinations in the imagined speech task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("dp" = ddpm_variant, "x_h" = x_hat, "deco" = decoder_variant,"u" = use,"n" = not use).

C.4 Loss combinations ablations

Configuration	SSVEP (Seen)				SSVEP (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
CE_a0.5_b0_g0	84.27 ± 1.34	84.20 ± 1.39	84.27 ± 1.34	99.39 ± 0.12	82.80 ± 5.98	82.45 ± 6.16	82.80 ± 5.98	98.95 ± 0.79
CE_a0.5_b0_gsched 0.2	84.27 ± 1.65	84.14 ± 1.72	84.27 ± 1.65	99.39 ± 0.13	81.62 ± 5.61	81.17 ± 5.81	81.62 ± 5.61	98.87 ± 0.81
CE_a0.5_bsched 0.05_g0	86.01 ± 0.86	85.99 ± 0.89	86.01 ± 0.86	99.48 ± 0.02	83.12 ± 5.75	82.68 ± 6.03	83.12 ± 5.75	98.89 ± 0.72
CE_a0.5_bsched 0.05_gsched 0.2	**86.40 ± 0.86**	**86.36 ± 0.92**	**86.40 ± 0.86**	**99.51 ± 0.04**	83.23 ± 4.69	82.79 ± 5.00	83.23 ± 4.69	**99.03 ± 0.64**
CE_a1_b0_g0	83.49 ± 1.72	83.38 ± 1.79	83.49 ± 1.72	99.32 ± 0.06	84.83 ± 4.91	84.56 ± 5.01	84.83 ± 4.91	99.02 ± 0.73
CE_a1_b0_gsched 0.2	84.46 ± 0.78	84.33 ± 0.87	84.46 ± 0.78	99.39 ± 0.08	83.44 ± 5.53	82.93 ± 5.88	83.44 ± 5.53	98.89 ± 0.82
CE_a1_bsched 0.05_g0	85.16 ± 0.95	85.14 ± 0.96	85.16 ± 0.95	99.40 ± 0.06	84.40 ± 6.22	84.14 ± 6.36	84.40 ± 6.22	98.94 ± 0.80
CE_a1_bsched 0.05_gsched 0.2	85.08 ± 1.53	84.95 ± 1.66	85.08 ± 1.53	99.37 ± 0.05	84.72 ± 6.04	84.44 ± 6.21	84.72 ± 6.04	98.90 ± 0.76
MSE_a0.5_b0_g0	85.39 ± 0.68	85.18 ± 0.90	85.39 ± 0.68	98.49 ± 0.10	**85.58 ± 8.39**	**85.49 ± 8.47**	**85.58 ± 8.39**	98.19 ± 1.02
MSE_a0.5_b0_gsched 0.2	84.97 ± 0.62	84.77 ± 0.61	84.97 ± 0.62	98.20 ± 0.16	84.83 ± 7.03	84.67 ± 7.26	84.83 ± 7.03	97.60 ± 1.65
MSE_a0.5_bsched 0.05_g0	84.50 ± 0.81	84.52 ± 0.81	84.50 ± 0.81	97.55 ± 0.45	80.24 ± 5.75	79.88 ± 5.74	80.24 ± 5.75	96.89 ± 1.73
MSE_a0.5_bsched 0.05_gsched 0.2	85.08 ± 0.76	85.09 ± 0.75	85.08 ± 0.76	97.30 ± 0.37	81.09 ± 6.84	80.92 ± 6.93	81.09 ± 6.84	96.69 ± 1.10
MSE_a1_b0_g0	85.66 ± 0.59	85.58 ± 0.68	85.66 ± 0.59	98.06 ± 0.11	85.26 ± 7.57	85.00 ± 7.62	85.26 ± 7.57	98.12 ± 1.14
MSE_a1_b0_gsched 0.2	85.70 ± 0.67	85.66 ± 0.68	85.70 ± 0.67	98.34 ± 0.12	84.62 ± 8.44	84.26 ± 8.72	84.62 ± 8.44	97.70 ± 1.60
MSE_a1_bsched .05_g0	86.21 ± 0.15	86.20 ± 0.11	86.21 ± 0.15	98.08 ± 0.27	83.44 ± 6.83	83.18 ± 6.94	83.44 ± 6.83	97.07 ± 2.09
MSE_a1_bsched 0.05_gsched 0.2	85.39 ± 0.15	85.37 ± 0.17	85.39 ± 0.15	98.10 ± 0.12	82.80 ± 6.19	82.48 ± 6.34	82.80 ± 6.19	97.45 ± 1.51

Table 18: Ablation study of loss in the SSVEP task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("sched" = scheduler to).

Configuration	P300 (Seen)				P300 (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
CE_a0.5_b0_g0	85.15 ± 1.25	61.34 ± 9.17	60.20 ± 6.39	72.13 ± 8.49	77.61 ± 5.30	59.52 ± 3.58	59.38 ± 2.61	66.68 ± 3.94
CE_a0.5_b0_gsched 0.2	84.96 ± 1.07	61.36 ± 8.67	60.18 ± 6.04	72.52 ± 8.40	77.15 ± 4.27	59.83 ± 3.08	60.14 ± 2.78	65.42 ± 3.51
CE_a0.5_bsched 0.05_g0	85.36 ± 1.01	62.19 ± 7.03	60.36 ± 4.98	76.10 ± 5.36	75.06 ± 2.99	61.63 ± 1.48	64.22 ± 1.48	70.90 ± 2.06
CE_a0.5_bsched 0.05_gsched 0.2	85.51 ± 1.09	65.01 ± 3.74	62.21 ± 3.11	78.48 ± 4.32	76.46 ± 1.12	**63.76 ± 0.81**	**66.84 ± 2.65**	**73.06 ± 2.84**
CE_a1_b0_g0	84.56 ± 0.95	65.49 ± 2.69	63.26 ± 2.83	77.34 ± 1.00	**80.18 ± 0.50**	63.07 ± 3.07	63.13 ± 4.36	71.95 ± 4.05
CE_a1_b0_gsched 0.2	83.91 ± 1.49	65.53 ± 1.16	**63.65 ± 1.92**	75.12 ± 0.99	78.19 ± 3.49	63.21 ± 3.97	63.99 ± 3.60	70.67 ± 5.66
CE_a1_bsched 0.05_g0	85.46 ± 0.75	**66.28 ± 2.44**	63.42 ± 2.23	**78.86 ± 2.41**	79.22 ± 2.47	63.35 ± 3.07	63.66 ± 2.95	71.34 ± 4.79
CE_a1_bsched 0.05_gsched 0.2	85.35 ± 1.12	64.39 ± 4.95	61.88 ± 4.10	77.14 ± 4.35	79.47 ± 0.54	63.67 ± 1.58	63.95 ± 1.86	70.79 ± 3.27
MSE_a0.5_b0_g0	84.70 ± 1.14	58.84 ± 9.64	58.44 ± 6.15	67.96 ± 9.11	67.08 ± 13.35	54.56 ± 7.66	57.93 ± 4.25	60.24 ± 4.85
MSE_a0.5_b0_gsched 0.2	83.90 ± 0.40	55.75 ± 7.38	55.99 ± 4.34	67.58 ± 8.14	63.50 ± 9.96	52.50 ± 6.04	56.70 ± 3.72	59.72 ± 4.79
MSE_a0.5_bsched 0.05_g0	**85.69 ± 0.65**	63.41 ± 3.27	60.73 ± 2.50	75.94 ± 2.75	74.81 ± 3.74	61.87 ± 1.89	65.58 ± 4.44	69.66 ± 5.34
MSE_a0.5_bsched 0.05_gsched 0.2	85.67 ± 0.52	65.01 ± 2.49	62.09 ± 2.09	75.30 ± 5.37	78.17 ± 1.62	61.83 ± 1.79	64.83 ± 3.56	68.73 ± 4.26
MSE_a1_b0_g0	84.24 ± 0.69	58.50 ± 9.22	58.31 ± 5.88	68.51 ± 8.11	68.46 ± 10.36	54.56 ± 6.82	56.33 ± 5.40	59.00 ± 6.62
MSE_a1_b0_gsched 0.2	84.68 ± 0.29	61.65 ± 1.34	59.45 ± 1.03	71.05 ± 1.04	72.24 ± 2.85	59.71 ± 3.64	63.42 ± 4.17	67.29 ± 5.38
MSE_a1_bsched 0.05_g0	85.20 ± 1.15	66.12 ± 1.40	63.29 ± 1.00	75.87 ± 2.28	72.83 ± 2.19	61.17 ± 1.95	65.55 ± 3.36	69.81 ± 3.62
MSE_a1_bsched 0.05_gsched 0.2	85.31 ± 0.56	64.17 ± 1.70	61.41 ± 1.32	75.70 ± 3.09	74.35 ± 2.84	61.78 ± 2.66	65.57 ± 5.00	69.59 ± 5.21

Table 19: Ablation study of loss in the P300 task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("sched" = scheduler to).

Configuration	MI (Seen)				MI (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
CE_a0.5_b0_g0	51.84 ± 2.36	47.19 ± 3.13	51.84 ± 2.36	81.38 ± 2.42	39.15 ± 7.00	37.98 ± 6.49	39.15 ± 7.00	66.57 ± 6.63
CE_a0.5_b0_gsched 0.2	53.87 ± 2.48	50.13 ± 3.19	53.87 ± 2.48	81.44 ± 1.65	39.99 ± 6.23	39.21 ± 5.71	39.99 ± 6.23	66.25 ± 6.73
CE_a0.5_bsched 0.05_g0	55.36 ± 2.11	53.21 ± 2.62	55.36 ± 2.11	**83.07 ± 1.54**	40.80 ± 6.38	39.21 ± 5.99	40.80 ± 6.38	67.29 ± 6.94
CE_a0.5_bsched 0.05_gsched 0.2	54.76 ± 3.08	52.67 ± 4.43	54.76 ± 3.08	83.06 ± 1.33	40.48 ± 6.61	39.39 ± 6.28	40.48 ± 6.61	**67.68 ± 6.98**
CE_a1_b0_g0	52.38 ± 3.19	48.02 ± 3.37	52.38 ± 3.19	81.50 ± 2.66	39.15 ± 4.69	37.77 ± 4.16	39.15 ± 4.69	65.42 ± 5.19
CE_a1_b0_gsched 0.2	51.44 ± 3.86	46.19 ± 4.98	51.44 ± 3.86	80.63 ± 3.05	39.18 ± 4.31	37.85 ± 3.56	39.18 ± 4.31	65.29 ± 5.10
CE_a1_bsched 0.05_g0	54.46 ± 2.59	52.02 ± 3.63	54.46 ± 2.59	82.65 ± 1.20	40.05 ± 7.45	38.91 ± 7.38	40.05 ± 7.45	67.01 ± 6.95
CE_a1_bsched 0.05_gsched 0.2	55.85 ± 2.80	54.25 ± 3.15	55.85 ± 2.80	82.72 ± 0.86	39.24 ± 7.95	38.07 ± 7.86	39.24 ± 7.95	66.70 ± 7.32
MSE_a0.5_b0_g0	53.92 ± 5.58	51.22 ± 8.61	53.92 ± 5.58	79.86 ± 4.12	37.33 ± 2.98	34.85 ± 1.05	37.33 ± 2.98	63.60 ± 4.09
MSE_a0.5_b0_gsched 0.2	53.62 ± 5.23	50.63 ± 7.83	53.62 ± 5.23	79.80 ± 4.09	37.59 ± 2.99	34.90 ± 1.34	37.59 ± 2.99	63.60 ± 3.91
MSE_a0.5_bsched 0.05_g0	57.74 ± 1.48	55.92 ± 2.94	57.74 ± 1.48	79.98 ± 2.41	40.89 ± 5.00	40.20 ± 4.83	40.89 ± 5.00	63.96 ± 3.68
MSE_a0.5_bsched 0.05_gsched 0.2	**59.67 ± 1.72**	**58.45 ± 2.70**	**59.67 ± 1.72**	81.22 ± 1.05	40.60 ± 4.03	39.56 ± 3.52	40.60 ± 4.03	63.57 ± 3.07
MSE_a1_b0_g0	54.07 ± 5.19	51.81 ± 8.05	54.07 ± 5.19	80.34 ± 3.07	37.30 ± 4.89	36.10 ± 4.59	37.30 ± 4.89	62.84 ± 5.47
MSE_a1_b0_gsched 0.2	54.91 ± 5.02	52.24 ± 7.49	54.91 ± 5.02	81.03 ± 3.28	37.33 ± 4.36	36.21 ± 4.11	37.33 ± 4.36	63.15 ± 4.89
MSE_a1_bsched 0.05_g0	57.79 ± 1.30	57.15 ± 1.89	57.79 ± 1.30	81.44 ± 2.13	39.32 ± 3.39	38.31 ± 2.84	39.32 ± 3.39	63.34 ± 3.57
MSE_a1_bsched 0.05_gsched 0.2	59.23 ± 1.58	57.85 ± 3.33	59.23 ± 1.58	82.16 ± 1.11	**41.44 ± 6.03**	**40.37 ± 6.26**	**41.44 ± 6.03**	65.18 ± 4.76

Table 20: Ablation study of loss in the MI task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("sched" = scheduler to).

Configuration	Imag. Speech (Seen)				Imag. Speech (Unseen)			
	Acc	F1	Recall	AUC	Acc	F1	Recall	AUC
CE_a0.5_b0_g0	17.83 ± 1.38	13.40 ± 2.54	17.80 ± 1.35	70.88 ± 1.42	13.26 ± 0.82	9.98 ± 1.14	13.26 ± 0.82	57.90 ± 2.93
CE_a0.5_b0_gsched 0.2	19.09 ± 0.75	**15.08 ± 0.99**	19.07 ± 0.78	72.13 ± 1.37	11.99 ± 2.87	9.08 ± 2.30	11.99 ± 2.87	**59.72 ± 1.83**
CE_a0.5_bsched 0.05_g0	18.46 ± 0.68	15.04 ± 0.64	18.43 ± 0.64	71.98 ± 0.72	11.24 ± 0.99	8.54 ± 1.38	11.24 ± 0.99	56.68 ± 3.58
CE_a0.5_bsched 0.05_gsched 0.2	**19.60 ± 1.62**	13.61 ± 1.07	**19.57 ± 1.59**	**73.49 ± 0.24**	9.34 ± 3.16	5.83 ± 1.34	9.34 ± 3.16	56.33 ± 3.92
CE_a1_b0_g0	18.08 ± 1.28	12.39 ± 0.35	18.06 ± 1.25	72.35 ± 0.89	11.49 ± 1.96	9.18 ± 2.13	11.49 ± 1.96	59.17 ± 1.89
CE_a1_b0_gsched 0.2	17.95 ± 0.70	13.52 ± 1.18	17.93 ± 0.71	73.07 ± 0.40	11.87 ± 1.53	8.18 ± 2.56	11.87 ± 1.53	59.12 ± 2.40
CE_a1_bsched 0.05_g0	17.44 ± 1.70	11.50 ± 0.76	17.42 ± 1.72	71.56 ± 2.03	12.12 ± 2.23	8.78 ± 1.11	12.12 ± 2.23	57.33 ± 3.33
CE_a1_bsched 0.05_gsched 0.2	15.55 ± 0.62	9.61 ± 1.23	15.53 ± 0.62	71.24 ± 1.66	11.62 ± 1.29	7.84 ± 1.32	11.62 ± 1.29	57.15 ± 3.18
MSE_a0.5_b0_g0	16.69 ± 1.32	11.20 ± 0.62	16.67 ± 1.35	66.83 ± 5.71	11.99 ± 0.47	8.54 ± 1.26	11.99 ± 0.47	55.95 ± 1.92
MSE_a0.5_b0_gsched 0.2	16.82 ± 1.98	11.22 ± 0.64	16.79 ± 1.96	64.87 ± 4.18	11.87 ± 1.39	7.68 ± 2.71	11.87 ± 1.39	54.02 ± 2.17
MSE_a0.5_bsched 0.05_g0	17.19 ± 0.81	10.68 ± 1.75	17.17 ± 0.78	70.09 ± 5.01	9.60 ± 1.53	5.44 ± 0.55	9.60 ± 1.53	52.43 ± 4.56
MSE_a0.5_bsched 0.05_gsched 0.2	17.32 ± 0.80	12.48 ± 1.70	17.33 ± 0.81	61.80 ± 7.84	11.62 ± 1.17	8.85 ± 1.36	11.62 ± 1.17	53.32 ± 0.93
MSE_a1_b0_g0	16.43 ± 0.98	12.53 ± 0.65	16.43 ± 0.99	62.13 ± 5.47	**13.51 ± 2.36**	**10.05 ± 1.92**	**13.51 ± 2.36**	53.55 ± 2.59
MSE_a1_b0_gsched 0.2	16.06 ± 2.01	11.90 ± 1.40	16.10 ± 2.04	65.92 ± 4.70	13.26 ± 1.93	9.80 ± 1.77	13.26 ± 1.93	54.53 ± 1.07
MSE_a1_bsched 0.05_g0	17.32 ± 1.11	12.89 ± 1.93	17.31 ± 1.11	61.35 ± 4.49	9.97 ± 2.52	6.64 ± 1.24	9.97 ± 2.52	50.25 ± 1.56
MSE_a1_bsched 0.05_gsched 0.2	17.57 ± 0.67	13.19 ± 1.56	17.58 ± 0.68	61.76 ± 4.09	12.12 ± 2.70	7.66 ± 2.48	12.12 ± 2.70	48.50 ± 1.67

Table 21: Ablation study of loss in the imagined speech task. Mean ± std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks ("sched" = scheduler to).

C.5 Mixup strategies ablations

Configuration (mixup layer/ warmup epoch/ random ratio)	SSVEP (Seen)				SSVEP (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
-1 / 100 / No	86.79 ± 1.75	86.75 ± 1.83	86.79 ± 1.75	**99.62 ± 0.02**	**85.26 ± 6.94**	85.02 ± 7.05	**85.26 ± 6.94**	**99.19 ± 0.81**
-1 / 100 / Yes	86.75 ± 0.78	86.74 ± 0.78	86.75 ± 0.78	99.60 ± 0.02	85.15 ± 7.46	**85.09 ± 7.32**	85.15 ± 7.46	99.16 ± 0.92
-1 / 150 / No	86.87 ± 1.77	86.86 ± 1.81	86.87 ± 1.77	99.55 ± 0.07	84.40 ± 7.65	84.07 ± 7.87	84.40 ± 7.65	99.02 ± 1.13
-1 / 150 / Yes	86.60 ± 0.42	86.62 ± 0.44	86.60 ± 0.42	99.54 ± 0.07	84.29 ± 7.09	84.08 ± 7.13	84.29 ± 7.09	99.06 ± 1.09
0 / 100 / No	86.60 ± 1.07	86.59 ± 1.08	86.60 ± 1.07	99.46 ± 0.13	84.51 ± 7.68	84.14 ± 7.92	84.51 ± 7.68	98.99 ± 1.12
0 / 100 / Yes	86.60 ± 1.12	86.56 ± 1.09	86.60 ± 1.12	99.58 ± 0.04	84.72 ± 6.48	84.54 ± 6.51	84.72 ± 6.48	99.15 ± 0.92
0 / 150 / No	87.36 ± 1.34	86.63 ± 0.54	86.64 ± 0.53	99.46 ± 0.11	83.65 ± 8.38	83.46 ± 8.44	83.65 ± 8.38	99.00 ± 1.11
0 / 150 / Yes	**87.84 ± 0.86**	**87.89 ± 0.83**	**87.84 ± 0.86**	99.58 ± 0.01	85.04 ± 7.94	84.85 ± 8.10	85.04 ± 7.94	99.11 ± 1.05
1 / 100 / No	85.08 ± 1.62	85.11 ± 1.62	85.08 ± 1.62	99.34 ± 0.13	84.51 ± 6.85	84.35 ± 6.91	84.51 ± 6.85	99.03 ± 0.97
1 / 100 / Yes	84.65 ± 2.36	84.57 ± 2.55	84.65 ± 2.36	99.40 ± 0.11	82.69 ± 5.94	82.52 ± 5.95	82.69 ± 5.94	98.98 ± 0.93
1 / 150 / No	85.47 ± 0.74	85.43 ± 0.82	85.47 ± 0.74	99.42 ± 0.07	83.33 ± 6.99	83.04 ± 7.16	83.33 ± 6.99	98.95 ± 1.12
1 / 150 / Yes	85.16 ± 0.66	85.09 ± 0.72	85.16 ± 0.66	99.42 ± 0.07	83.55 ± 7.21	83.31 ± 7.45	83.55 ± 7.21	99.00 ± 1.16
2 / 100 / No	85.12 ± 1.55	85.17 ± 1.52	85.12 ± 1.55	99.36 ± 0.12	84.19 ± 6.59	83.99 ± 6.61	84.19 ± 6.59	99.00 ± 0.95
2 / 100 / Yes	85.12 ± 2.06	84.90 ± 2.59	85.12 ± 2.06	99.44 ± 0.15	84.40 ± 7.59	84.26 ± 7.71	84.40 ± 7.59	99.12 ± 0.79
2 / 150 / No	85.47 ± 0.74	85.43 ± 0.82	85.47 ± 0.74	99.42 ± 0.07	83.33 ± 6.99	82.38 ± 6.55	83.33 ± 6.99	98.95 ± 1.12
2 / 150 / Yes	84.89 ± 0.91	84.80 ± 0.97	84.89 ± 0.91	99.43 ± 0.05	83.97 ± 7.70	83.74 ± 7.94	83.97 ± 7.70	98.99 ± 1.15
3 / 100 / No	84.77 ± 2.16	84.72 ± 2.28	84.77 ± 2.16	99.36 ± 0.12	83.01 ± 5.99	82.84 ± 6.01	83.01 ± 5.99	99.03 ± 0.97
3 / 100 / Yes	84.65 ± 2.36	84.57 ± 2.55	84.65 ± 2.36	99.40 ± 0.11	82.69 ± 5.94	82.52 ± 5.95	82.69 ± 5.94	98.98 ± 0.93
3 / 150 / No	85.47 ± 0.74	85.43 ± 0.82	85.47 ± 0.74	99.42 ± 0.07	83.33 ± 6.99	83.04 ± 7.16	83.33 ± 6.99	98.95 ± 1.12
3 / 150 / Yes	85.47 ± 0.74	85.43 ± 0.82	85.47 ± 0.74	99.42 ± 0.07	83.33 ± 6.99	83.04 ± 7.16	83.33 ± 6.99	98.95 ± 1.12
4 / 100 / No	85.70 ± 1.50	85.70 ± 1.61	85.70 ± 1.50	99.42 ± 0.13	83.76 ± 8.14	83.60 ± 8.15	83.76 ± 8.14	98.98 ± 1.07
4 / 100 / Yes	84.85 ± 2.53	84.84 ± 2.78	84.85 ± 2.53	99.39 ± 0.10	82.26 ± 6.60	82.14 ± 6.54	82.26 ± 6.60	99.02 ± 0.86
4 / 150 / No	85.78 ± 1.34	85.81 ± 1.44	85.78 ± 1.34	99.43 ± 0.08	83.23 ± 6.91	83.01 ± 6.78	83.23 ± 6.91	99.02 ± 1.03
4 / 150 / Yes	85.55 ± 0.82	85.56 ± 0.95	85.55 ± 0.82	99.46 ± 0.11	83.33 ± 6.99	82.99 ± 7.24	83.33 ± 6.99	99.08 ± 0.91

Table 22: Ablation study of mixup in the SSVEP task. Mean±std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks (mixup layer: -1 = temporal mixup at input, 0 = weighted average at input, 1/2/3 = weighted average after first/second/third encoder layer, 4 = weighted average after attention pooling. warmup epoch: number of epochs to train the generators before training the classifier. random ratio: No = equal possibility on choosing ddpm or decoder out for temporal mixup/equal weight for weighted average mixup, Yes = beta/dirichlet distribution with b=0.2 for a random ratio more heavily tilted towards one of the mixup candidates).

Configuration (mixup layer/ warmup epoch/ random ratio)	P300 (Seen)				P300 (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
-1 / 100 / No	85.61 ± 0.52	67.30 ± 1.54	64.42 ± 2.02	**80.00 ± 1.39**	**79.56 ± 4.43**	65.19 ± 7.51	66.10 ± 7.91	72.72 ± 9.74
-1 / 100 / Yes	85.58 ± 0.47	**67.89 ± 0.71**	**64.98 ± 0.71**	79.94 ± 1.61	79.51 ± 4.51	**65.22 ± 7.57**	66.18 ± 7.97	73.41 ± 9.22
-1 / 150 / No	85.70 ± 0.28	66.38 ± 0.92	63.30 ± 0.84	78.55 ± 1.24	78.05 ± 6.49	64.40 ± 7.89	65.74 ± 7.33	71.71 ± 9.98
-1 / 150 / Yes	**85.78 ± 0.13**	66.30 ± 0.51	63.18 ± 0.56	79.05 ± 0.35	79.10 ± 2.04	64.31 ± 5.87	65.65 ± 7.85	71.52 ± 9.12
0 / 100 / No	85.70 ± 0.44	66.60 ± 1.84	63.59 ± 1.88	78.87 ± 1.90	78.25 ± 6.85	64.98 ± 8.43	66.65 ± 8.39	72.34 ± 10.36
0 / 100 / Yes	85.54 ± 0.19	66.38 ± 1.54	63.43 ± 1.47	79.63 ± 1.54	75.11 ± 5.28	63.41 ± 6.66	67.46 ± 8.57	73.52 ± 10.37
0 / 150 / No	**85.78 ± 0.41**	67.00 ± 1.29	63.91 ± 1.27	78.73 ± 1.45	78.10 ± 6.48	64.64 ± 8.28	66.21 ± 8.24	72.06 ± 10.14
0 / 150 / Yes	85.66 ± 0.25	66.60 ± 0.89	63.55 ± 0.81	79.48 ± 1.97	75.81 ± 3.96	63.38 ± 6.33	66.85 ± 8.63	72.89 ± 10.04
1 / 100 / No	85.03 ± 0.33	62.05 ± 2.81	59.77 ± 2.19	76.15 ± 1.21	70.27 ± 3.61	59.38 ± 3.95	64.29 ± 4.65	68.67 ± 5.30
1 / 100 / Yes	85.48 ± 0.19	66.53 ± 1.64	63.66 ± 1.84	79.16 ± 1.17	66.82 ± 3.51	58.12 ± 1.03	66.45 ± 5.63	72.31 ± 8.49
1 / 150 / No	85.02 ± 0.91	61.30 ± 5.42	59.35 ± 4.08	74.17 ± 5.60	72.35 ± 3.03	60.51 ± 3.10	64.56 ± 3.92	69.57 ± 5.41
1 / 150 / Yes	85.23 ± 0.99	64.38 ± 5.42	61.93 ± 4.45	77.76 ± 3.93	71.72 ± 2.41	60.98 ± 3.39	66.22 ± 4.78	71.21 ± 6.19
2 / 100 / No	84.55 ± 0.97	56.75 ± 4.83	56.75 ± 4.83	71.05 ± 10.48	70.83 ± 1.12	58.46 ± 0.39	62.09 ± 1.45	66.24 ± 2.34
2 / 100 / Yes	84.84 ± 0.80	61.74 ± 5.07	59.71 ± 3.79	76.45 ± 3.50	72.20 ± 1.37	60.54 ± 2.63	64.91 ± 4.27	70.24 ± 5.46
2 / 150 / No	84.73 ± 0.75	60.25 ± 4.67	58.52 ± 3.42	74.52 ± 5.66	74.35 ± 0.65	61.03 ± 2.28	63.97 ± 4.40	68.81 ± 5.90
2 / 150 / Yes	84.87 ± 0.79	62.09 ± 5.56	60.04 ± 4.15	74.71 ± 5.79	73.87 ± 0.18	61.51 ± 2.21	65.20 ± 4.06	70.76 ± 5.20
3 / 100 / No	84.86 ± 0.44	61.05 ± 1.52	58.93 ± 1.09	76.08 ± 0.75	70.95 ± 4.27	60.24 ± 4.92	65.37 ± 5.98	69.56 ± 7.12
3 / 100 / Yes	85.16 ± 0.17	65.07 ± 2.10	62.40 ± 2.02	78.23 ± 1.34	71.84 ± 6.59	62.04 ± 7.10	**67.89 ± 7.38**	73.22 ± 9.40
3 / 150 / No	84.99 ± 0.41	59.77 ± 1.62	59.77 ± 1.62	76.95 ± 1.70	72.01 ± 4.05	61.35 ± 5.41	66.56 ± 6.89	71.09 ± 8.62
3 / 150 / Yes	85.27 ± 0.45	62.82 ± 3.39	60.39 ± 2.83	77.27 ± 1.96	73.99 ± 4.67	62.18 ± 5.96	66.33 ± 7.83	71.19 ± 10.09
4 / 100 / No	85.47 ± 0.11	65.16 ± 2.15	62.30 ± 1.91	78.26 ± 1.36	72.84 ± 5.44	62.07 ± 5.67	67.37 ± 7.83	72.55 ± 8.94
4 / 100 / Yes	85.48 ± 0.07	65.64 ± 1.41	62.72 ± 1.34	79.56 ± 0.34	76.03 ± 0.72	63.23 ± 4.99	67.16 ± 9.38	**73.91 ± 9.71**
4 / 150 / No	85.00 ± 0.91	62.81 ± 6.22	60.69 ± 4.74	75.11 ± 6.29	74.24 ± 2.88	61.90 ± 3.60	65.40 ± 4.55	71.28 ± 5.96
4 / 150 / Yes	85.26 ± 0.59	64.19 ± 3.92	61.60 ± 3.19	77.58 ± 2.92	75.38 ± 4.29	62.57 ± 4.95	65.28 ± 4.82	71.59 ± 6.93

Table 23: Ablation study of mixup in the P300 task. Mean±std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks (mixup layer: -1 = temporal mixup at input, 0 = weighted average at input, 1/2/3 = weighted average after first/second/third encoder layer, 4 = weighted average after attention pooling. warmup epoch: number of epochs to train the generators before training the classifier. random ratio: No = equal possibility on choosing ddpm or decoder out for temporal mixup/equal weight for weighted average mixup, Yes = beta/dirichlet distribution with b=0.2 for a random ratio more heavily tilted towards one of the mixup candidates).

Configuration (mixup layer/ warmup epoch/ random ratio)	MI (Seen)				MI (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
-1 / 100 / No	57.69 ± 3.27	55.70 ± 4.59	57.69 ± 3.27	84.97 ± 1.19	36.78 ± 5.22	35.94 ± 5.62	36.78 ± 5.22	63.44 ± 5.17
-1 / 100 / Yes	58.33 ± 2.10	56.58 ± 3.53	58.33 ± 2.10	84.52 ± 1.20	36.23 ± 5.56	35.56 ± 5.90	36.23 ± 5.56	63.44 ± 5.01
-1 / 150 / No	58.13 ± 4.14	56.10 ± 5.03	58.13 ± 4.14	85.32 ± 1.64	35.53 ± 3.03	34.51 ± 3.21	35.53 ± 3.03	62.92 ± 3.83
-1 / 150 / Yes	57.44 ± 4.36	55.81 ± 5.18	57.44 ± 4.36	85.03 ± 2.00	36.49 ± 5.74	35.68 ± 6.36	36.49 ± 5.74	63.62 ± 5.23
0 / 100 / No	62.75 ± 6.07	62.71 ± 5.90	62.75 ± 6.07	85.84 ± 4.03	36.83 ± 8.41	36.01 ± 8.52	36.83 ± 8.41	63.51 ± 6.71
0 / 100 / Yes	62.25 ± 3.33	62.32 ± 3.18	62.25 ± 3.33	86.28 ± 2.31	38.14 ± 8.56	37.99 ± 8.69	38.14 ± 8.56	63.64 ± 5.84
0 / 150 / No	**63.44 ± 3.44**	**63.44 ± 3.36**	**63.44 ± 3.44**	**87.20 ± 2.69**	35.45 ± 6.82	34.63 ± 6.56	35.45 ± 6.82	62.40 ± 5.07
0 / 150 / Yes	62.95 ± 5.94	62.97 ± 5.95	62.95 ± 5.94	86.71 ± 3.13	36.17 ± 6.50	35.66 ± 6.94	36.17 ± 6.50	63.10 ± 5.78
1 / 100 / No	59.38 ± 3.80	59.38 ± 3.80	59.38 ± 3.80	83.61 ± 2.36	36.08 ± 4.55	35.17 ± 5.20	36.08 ± 4.55	63.93 ± 5.77
1 / 100 / Yes	61.56 ± 3.06	61.43 ± 3.04	61.56 ± 3.06	85.52 ± 1.81	37.15 ± 7.61	37.02 ± 7.84	37.15 ± 7.61	63.38 ± 6.53
1 / 150 / No	60.37 ± 2.25	60.50 ± 2.29	60.37 ± 2.25	84.62 ± 1.70	36.34 ± 6.36	35.71 ± 6.82	36.34 ± 6.36	62.81 ± 4.85
1 / 150 / Yes	62.35 ± 4.00	62.42 ± 4.01	62.35 ± 4.00	86.41 ± 2.23	36.63 ± 5.51	36.44 ± 5.79	36.63 ± 5.51	63.27 ± 5.17
2 / 100 / No	59.13 ± 1.21	58.48 ± 1.39	59.13 ± 1.21	84.00 ± 1.30	36.95 ± 5.34	36.40 ± 5.15	36.95 ± 5.34	63.50 ± 5.68
2 / 100 / Yes	58.58 ± 2.26	58.41 ± 2.03	58.58 ± 2.26	83.91 ± 2.18	37.82 ± 5.87	37.69 ± 5.88	37.82 ± 5.87	63.69 ± 5.22
2 / 150 / No	57.74 ± 1.79	57.12 ± 1.01	57.74 ± 1.79	83.61 ± 1.38	**38.83 ± 7.09**	**38.71 ± 7.33**	**38.83 ± 7.09**	**64.79 ± 6.40**
2 / 150 / Yes	61.16 ± 2.46	61.03 ± 2.62	61.16 ± 2.46	85.02 ± 0.98	36.46 ± 6.26	36.53 ± 6.41	36.46 ± 6.26	62.82 ± 5.49
3 / 100 / No	59.77 ± 3.53	59.26 ± 3.93	59.77 ± 3.53	83.27 ± 1.17	36.86 ± 6.21	36.42 ± 6.34	36.86 ± 6.21	63.59 ± 6.18
3 / 100 / Yes	60.07 ± 1.21	59.72 ± 0.76	60.07 ± 1.21	84.79 ± 1.44	37.88 ± 7.69	37.73 ± 7.67	37.88 ± 7.69	63.69 ± 5.73
3 / 150 / No	59.67 ± 4.03	59.30 ± 4.29	59.67 ± 4.03	84.50 ± 2.93	36.72 ± 3.88	36.70 ± 4.28	36.72 ± 3.88	63.31 ± 3.79
3 / 150 / Yes	60.81 ± 3.74	60.61 ± 3.77	60.81 ± 3.74	84.25 ± 2.34	37.36 ± 5.16	37.32 ± 5.27	37.36 ± 5.16	63.37 ± 5.07
4 / 100 / No	57.94 ± 2.28	56.67 ± 0.50	57.94 ± 2.28	84.04 ± 1.48	36.40 ± 3.79	36.01 ± 3.93	36.40 ± 3.79	63.75 ± 3.65
4 / 100 / Yes	58.23 ± 4.14	57.97 ± 3.77	58.23 ± 4.14	84.10 ± 2.88	37.15 ± 5.17	36.69 ± 5.45	37.15 ± 5.17	63.87 ± 4.77
4 / 150 / No	58.33 ± 3.37	57.92 ± 2.86	58.33 ± 3.37	84.05 ± 2.06	37.96 ± 5.57	37.06 ± 5.58	37.96 ± 5.57	64.10 ± 4.85
4 / 150 / Yes	57.79 ± 4.99	56.75 ± 4.50	57.79 ± 4.99	84.08 ± 3.49	36.69 ± 6.35	36.61 ± 6.49	36.69 ± 6.35	63.53 ± 5.17

Table 24: Ablation study of mixup in the MI task. Mean±std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks (mixup layer: -1 = temporal mixup at input, 0 = weighted average at input, 1/2/3 = weighted average after first/second/third encoder layer, 4 = weighted average after attention pooling. warmup epoch: number of epochs to train the generators before training the classifier. random ratio: No = equal possibility on choosing ddpm or decoder out for temporal mixup/equal weight for weighted average mixup, Yes = beta/dirichlet distribution with b=0.2 for a random ratio more heavily tilted towards one of the mixup candidates).

Configuration (mixup layer/ warmup epoch/ random ratio)	Imagined Speech (Seen)				Imagined Speech (Unseen)			
	Acc (%)	F1 (%)	Recall (%)	AUC (%)	Acc (%)	F1 (%)	Recall (%)	AUC (%)
-1 / 100 / No	17.57 ± 1.17	12.24 ± 3.26	17.55 ± 1.16	73.01 ± 0.91	**12.12 ± 0.38**	7.77 ± 1.27	**12.12 ± 0.38**	55.73 ± 2.77
-1 / 100 / Yes	17.32 ± 2.69	11.18 ± 4.16	17.30 ± 2.69	**73.64 ± 1.56**	10.86 ± 1.43	6.80 ± 0.49	10.86 ± 1.43	**57.63 ± 0.34**
-1 / 150 / No	18.08 ± 0.42	11.48 ± 2.44	18.06 ± 0.44	73.07 ± 0.81	11.87 ± 0.79	7.43 ± 0.65	11.87 ± 0.79	56.82 ± 1.54
-1 / 150 / Yes	18.46 ± 1.07	11.88 ± 3.10	18.43 ± 1.09	73.20 ± 0.72	11.62 ± 1.22	7.19 ± 0.74	11.62 ± 1.22	56.62 ± 1.89
0 / 100 / No	17.19 ± 0.62	11.74 ± 1.58	17.17 ± 0.58	73.14 ± 0.75	11.36 ± 1.00	7.50 ± 0.70	11.36 ± 1.00	56.25 ± 2.15
0 / 100 / Yes	**19.47 ± 0.95**	**14.70 ± 0.60**	**19.44 ± 0.95**	71.90 ± 1.82	11.62 ± 1.43	**9.29 ± 0.89**	11.62 ± 1.43	53.80 ± 2.29
0 / 150 / No	17.57 ± 0.46	10.97 ± 1.65	17.55 ± 0.44	72.96 ± 0.91	11.87 ± 0.79	7.47 ± 0.66	11.87 ± 0.79	56.72 ± 1.71
0 / 150 / Yes	16.31 ± 1.40	11.45 ± 0.58	16.29 ± 1.37	72.38 ± 1.63	10.35 ± 2.09	6.11 ± 1.09	10.35 ± 2.09	54.91 ± 2.51
1 / 100 / No	18.08 ± 1.77	13.16 ± 3.38	18.06 ± 1.79	72.47 ± 3.16	11.24 ± 2.52	8.33 ± 2.28	11.24 ± 2.52	55.49 ± 1.96
1 / 100 / Yes	18.08 ± 0.42	10.55 ± 1.10	18.06 ± 0.44	73.19 ± 0.73	10.73 ± 2.74	7.45 ± 0.65	10.73 ± 2.74	55.25 ± 4.22
1 / 150 / No	17.95 ± 1.71	13.77 ± 3.24	17.93 ± 1.71	72.17 ± 1.62	9.72 ± 2.66	6.59 ± 0.17	9.72 ± 2.66	54.45 ± 3.34
1 / 150 / Yes	17.19 ± 1.11	10.51 ± 1.05	17.17 ± 1.09	73.00 ± 0.88	11.62 ± 1.22	6.55 ± 1.61	11.62 ± 1.22	55.87 ± 3.15
2 / 100 / No	17.45 ± 0.41	12.91 ± 1.93	17.42 ± 0.38	71.57 ± 2.51	10.23 ± 1.97	6.84 ± 0.55	10.23 ± 1.97	55.16 ± 2.83
2 / 100 / Yes	16.94 ± 0.98	11.57 ± 0.78	16.92 ± 0.95	72.98 ± 0.88	11.87 ± 1.43	7.37 ± 2.88	11.87 ± 1.43	55.90 ± 3.18
2 / 150 / No	16.94 ± 0.98	11.96 ± 1.46	16.92 ± 0.95	72.48 ± 1.47	11.11 ± 1.22	5.91 ± 0.97	11.11 ± 1.22	54.66 ± 2.50
2 / 150 / Yes	17.19 ± 1.11	10.51 ± 1.05	17.17 ± 1.09	73.00 ± 0.88	11.62 ± 1.22	6.55 ± 1.61	11.62 ± 1.22	55.87 ± 3.15
3 / 100 / No	17.45 ± 0.70	14.12 ± 0.68	17.42 ± 0.66	71.25 ± 1.86	9.47 ± 1.65	8.07 ± 1.49	9.47 ± 1.65	52.88 ± 1.35
3 / 100 / Yes	17.07 ± 1.03	11.79 ± 1.17	17.05 ± 1.00	73.38 ± 0.86	11.49 ± 1.16	6.76 ± 1.91	11.49 ± 1.16	55.63 ± 2.91
3 / 150 / No	16.06 ± 0.20	11.54 ± 1.04	16.04 ± 0.22	71.23 ± 1.65	11.11 ± 0.79	6.73 ± 1.63	11.11 ± 0.79	53.75 ± 1.70
3 / 150 / Yes	16.44 ± 1.26	9.43 ± 2.92	16.41 ± 1.22	72.50 ± 1.45	11.74 ± 1.31	5.30 ± 1.29	11.74 ± 1.31	57.20 ± 4.91
4 / 100 / No	16.56 ± 1.13	10.92 ± 0.36	16.54 ± 1.09	73.15 ± 0.81	11.49 ± 1.16	6.92 ± 2.16	11.49 ± 1.16	54.95 ± 2.52
4 / 100 / Yes	17.19 ± 1.11	10.51 ± 1.05	17.17 ± 1.09	73.00 ± 0.88	11.62 ± 1.22	6.55 ± 1.61	11.62 ± 1.22	55.87 ± 3.15
4 / 150 / No	16.44 ± 1.26	11.07 ± 0.13	16.41 ± 1.22	71.59 ± 2.89	10.35 ± 2.09	5.38 ± 1.20	10.35 ± 2.09	54.50 ± 2.53
4 / 150 / Yes	17.19 ± 1.11	10.51 ± 1.05	17.17 ± 1.09	73.00 ± 0.88	11.62 ± 1.22	6.55 ± 1.61	11.62 ± 1.22	55.87 ± 3.15

Table 25: Ablation study of mixup in the Imagined Speech task. Mean±std is reported separately for Accuracy, F1, Recall, and AUC on seen- and unseen-subject test splits across four tasks (mixup layer: -1 = temporal mixup at input, 0 = weighted average at input, 1/2/3 = weighted average after first/second/third encoder layer, 4 = weighted average after attention pooling. warmup epoch: number of epochs to train the generators before training the classifier. random ratio: No = equal possibility on choosing ddpm or decoder out for temporal mixup/equal weight for weighted average mixup, Yes = beta/dirichlet distribution with b=0.2 for a random ratio more heavily tilted towards one of the mixup candidates).

D Complete statistical reporting results

D.1 Methodology

EEG decoding suffers from low statistical power due to extreme inter-subject variability, limited trial counts, and costly LOSO evaluation [20, 14]. In our runs with three independent seeds, standard tests (Wilcoxon, permutation) often returned p-values near 1.0, masking reproducible gains, which is an expected outcome in such low-n, high-variance settings [39, 29]. We therefore propose a complementary framework emphasizing effect size estimation and evidence synthesis over binary significance. This approach quantifies improvement magnitude and consistency across seeds and datasets, retaining sensitivity to systematic trends even when classical tests fail, in line with best practices for robust neural decoding [39, 29].

For each comparison between configurations c_1 and c_2, we compute Cohen's d and its 95% confidence interval:

$$d = \frac{\bar{x}_{c_1} - \bar{x}_{c_2}}{s_{\text{pooled}}}, \quad \text{CI}_{95\%} = d \pm t_{\alpha/2, df} \cdot \text{SE}_d,$$

where the standard error is

$$\text{SE}_d = \sqrt{\frac{n_1 + n_2}{n_1 n_2} + \frac{d^2}{2(n_1 + n_2)}}.$$

A win is established through hierarchical evidence assessment based on cross-seed consistency and effect magnitude. For configurations with complete cross-seed agreement (i.e., all seeds exhibit consistent directional differences), evidence strength is defined as follows: (1) strong evidence requires both a large effect size ($|d| \geq 0.5$) and a meaningful relative improvement of at least 2%; (2) moderate evidence requires either a large effect size ($|d| \geq 0.5$) or a relative improvement of at least 2%; (3) weak evidence requires a medium effect size ($|d| \geq 0.3$); (4) minimal evidence requires a small effect size ($|d| \geq 0.2$). For configurations exhibiting majority cross-seed agreement (i.e., at least 2 out of 3 seeds show consistent direction), all evidence categories are downgraded by one level. Configuration c_1 is considered to exhibit superior performance over c_2 if any evidence category is satisfied.

To summarize model comparisons, we construct a win-loss matrix $\mathbf{W}$ where $W_{ij} = 1$ if configuration i shows evidence of superiority over configuration j. The win rate of configuration c_i is computed as

$$\text{WinRate}_i = \frac{\sum_j W_{ij}}{\sum_j (W_{ij} + W_{ji})}.$$

This matrix supports a global ranking across all configurations.

As a complementary analysis, we compute posterior probabilities $P(\text{left})$, $P(\text{rope})$, and $P(\text{right})$ using the `baycomp` framework with ROPE threshold $\rho = 0.01$. Configuration c_1 is considered to have Bayesian evidence of superiority if $P(\text{right}) > 0.85$.

D.2 Results

Practical evidence assessments

Bayesian evidence assessment

Due to page limitations, only SSVEP task results are shown.

Wilcoxon signed rank tests and permutation tests

Due to minimal statistical significance after correction, only one complete analytical framework applied to SSVEP ablation results is presented as a demonstrative example, constrained by page limitations

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
x_hat + skips	6	0	6	1.00	skips, x + x_hat, z + skips, z + x, z + x_hat, z only	—	Weak:3, Minimal:2, Moderate:1	4	2	6	0.667	x + skips, x + x_hat + skips, z + x, z + x_hat	x + x_hat, z only	Minimal:2, Strong:1, Weak:1
x + x_hat + skips	7	0	7	1.00	skips, x + skips, x + x_hat, z + skips, z + x, z + x_hat, z only	—	Weak:3, Moderate:2, Strong:1, Minimal:1	2	3	5	0.40	x + skips, z + x	x + x_hat, x_hat + skips, z only	Moderate:2
x + skips	5	1	6	0.833	skips, x + x_hat, z + skips, z + x, z + x_hat	x + x_hat + skips	Minimal:2, Weak:2, Moderate:1	0	6	6	0.00	—	x + x_hat, x + x_hat + skips, x_hat + skips, z + skips, z + x_hat, z only	—
z + skips	2	3	5	0.40	skips, z + x	x + skips, x + x_hat + skips, x_hat + skips	Weak:1, Minimal:1	3	2	5	0.60	skips, x + skips, z + x	x + x_hat, z only	Moderate:2, Weak:1
x + x_hat	2	3	5	0.40	skips, z + x	x + skips, x + x_hat + skips, x_hat + skips	Moderate:1, Weak:1	7	0	7	1.00	skips, x + skips, x + x_hat + skips, x_hat + skips, z + skips, z + x, z + x_hat	—	Moderate:3, Strong:2, Minimal:1, Weak:1
z only	1	2	3	0.333	skips	x + x_hat + skips, x_hat + skips	Moderate:1	7	0	7	1.00	skips, x + skips, x + x_hat + skips, x_hat + skips, z + skips, z + x, z + x_hat	—	Strong:3, Weak:2, Minimal:1, Moderate:1
z + x_hat	1	3	4	0.25	skips	x + skips, x + x_hat + skips, x_hat + skips	Weak:1	1	3	4	0.25	x + skips	x + x_hat, x_hat + skips, z only	Minimal:1
z + x	1	5	6	0.167	skips	x + skips, x + x_hat, x + x_hat + skips, x_hat + skips, z + skips	Weak:1	0	5	5	0.00	—	x + x_hat, x + x_hat + skips, x_hat + skips, z + skips, z only	—
skips	0	8	8	0.00	—	x + skips, x + x_hat, x + x_hat + skips, x_hat + skips, z + skips, z + x, z + x_hat, z only	—	0	3	3	0.00	—	x + x_hat, z + skips, z only	—

Table 26: Practical evidence assessment of decoder input ablations in the SSVEP task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
eegnet_classifier__x	6	0	6	1.00	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat, fc_classifier__z	—	Strong:6	5	1	6	0.83	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	fc_classifier__z	Strong:5
fc_classifier__z	5	1	6	0.83	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x	Strong:5	6	0	6	1.00	eegnet_classifier__decoder_out, eegnet_classifier__x, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	—	Strong:6
eegnet_classifier__decoder_out	4	2	6	0.67	eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x, fc_classifier__z	Strong:4	4	2	6	0.67	eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x, fc_classifier__z	Strong:3, Weak:1
fc_classifier__decoder_out	3	3	6	0.50	eegnet_classifier__x_hat, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__z	Strong:3	3	3	6	0.50	eegnet_classifier__x_hat, fc_classifier__x	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__z	Strong:3
eegnet_classifier__x_hat	1	4	5	0.20	fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Strong:1	1	5	6	0.17	fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Moderate:1
fc_classifier__x	1	4	5	0.20	fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Strong:1	2	4	6	0.33	eegnet_classifier__x_hat, fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Moderate:1, Strong:1
fc_classifier__x_hat	0	6	6	0.00	—	eegnet_classifier__decoder_out, eegnet_classifier__x, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__z	—	0	6	6	0.00	—	eegnet_classifier__decoder_out, eegnet_classifier__x, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__z	—

Table 27: Practical evidence assessment of classifier type ablations in the SSVEP task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
no_ddpm_x_no_decoder	5	0	5	1.00	no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:4 Minimal:1	4	0	4	1.00	use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:3 Moderate:1
no_ddpm_x_use_decoder	4	1	5	0.80	use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder	Strong:4	3	0	3	1.00	use_ddpm_x_no_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:2 Minimal:1
use_ddpm_x_no_decoder	3	2	5	0.60	use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder	Strong:2 Minimal:1	2	3	5	0.40	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder	Strong:2
use_ddpm_x_use_decoder	2	3	5	0.40	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder	Strong:2	3	1	4	0.75	use_ddpm_x_no_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder	Strong:2 Moderate:1
use_ddpm_x_hat_no_decoder	1	4	5	0.20	use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder	Weak:1	0	5	5	0.00	—	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_use_decoder	—
use_ddpm_x_hat_use_decoder	0	5	5	0.00	—	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder	—	1	4	5	0.20	use_ddpm_x_hat_no_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder	Weak:1

Table 28: Practical evidence assessment of architecture ablations in the SSVEP task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
layer-1_randNo	**8**	0	8	**1.00**	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Strong:5, Moderate:2, Weak:1	**8**	0	8	**1.00**	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Strong:5, Moderate:2, Weak:1
layer-1_randYes	**9**	0	9	**1.00**	layer0_randNo, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Moderate:3, Strong:3, Weak:2, Minimal:1	**9**	0	9	**1.00**	layer0_randNo, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Moderate:3, Strong:3, Weak:2, Minimal:1
layer0_randYes	**8**	0	8	**1.00**	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Moderate:4, Weak:2, Minimal:2	**8**	0	8	**1.00**	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Moderate:4, Weak:2, Minimal:2
layer0_randNo	**8**	1	9	**0.89**	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	layer-1_randYes	Moderate:3, Strong:3, Weak:2	**8**	1	9	**0.89**	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	layer-1_randYes	Moderate:3, Strong:3, Weak:2
layer4_randNo	7	4	11	0.64	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes	Weak:7	7	4	11	0.64	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes	Weak:7
layer2_randYes	3	5	8	0.38	layer1_randYes, layer3_randNo, layer3_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	Weak:3	3	5	8	0.38	layer1_randYes, layer3_randNo, layer3_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	Weak:3
layer1_randYes	0	6	6	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo	—	0	6	6	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo	—
layer1_randNo	0	5	5	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	—	0	5	5	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	—
layer2_randNo	0	5	5	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	—	0	5	5	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	—
layer3_randNo	0	6	6	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo	—	0	6	6	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo	—
layer3_randYes	0	6	6	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo	—	0	6	6	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo	—
layer4_randYes	0	5	5	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	—	0	5	5	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randNo	—

Table 29: Practical evidence assessment of mixup ablations in the SSVEP task. Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
CE_a0.5_bscheduler to 0.05_gscheduler to 0.2	**14**	0	14	**1.00**	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—	Strong:5, Moderate:4, Weak:4, Minimal:1	3	6	9	0.33	CE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_b0_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a1_b0_g0, CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0, Strong:1	
MSE_a1_bscheduler to 0.05_g0	**13**	0	13	**1.00**	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—	Moderate:6, Weak:4, Strong:3	4	7	11	0.36	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a1_b0_g0, CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,Minimal:1,Strong:1	
CE_a0.5_bscheduler to 0.05_g0	**13**	1	14	**0.93**	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_gscheduler to 0.2	Weak:5, Moderate:4, Strong:3, Minimal:1	5	8	13	0.38	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_gscheduler to 0.2	Strong:2, Minimal:1, Moderate:1, Weak:1
MSE_a1_b0_g0	11	3	14	0.79	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, MSE_a1_bscheduler to 0.05_g0	Moderate:4, Weak:4, Minimal:2, Strong:1	**12**	0	12	**1.00**	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—	Strong:6, Moderate:3, Weak:2, Minimal:1
MSE_a1_b0_gscheduler to 0.2	9	3	12	0.75	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.05_gscheduler to 0.2, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, MSE_a1_bscheduler to 0.05_g0	Moderate:4, Weak:2, Minimal:2, Strong:1	8	2	10	0.80	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_gscheduler to 0.2	MSE_a0.5_b0_g0, MSE_a1_b0_g0	Moderate:3, Minimal:2, Strong:2, Weak:1
MSE_a0.5_b0_g0	6	4	10	0.60	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_gscheduler to 0.2,CE_a1_b0_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_bscheduler to 0.05_g0	Weak:4, Moderate:2	**11**	0	11	**1.00**	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—	Moderate:7, Strong:2, Minimal:1, Weak:1

Table 30: Practical evidence assessment of loss ablations in the SSVEP task (Part 1 of 3). Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

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Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
MSE_a1_bscheduler to 0.05_gscheduler to 0.2	7	5	12	0.58	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_b0_gscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_bscheduler to 0.05_g0	Weak:4, Minimal:2, Moderate:1	3	9	12	0.25	CE_a0.5_b0_gscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.2,MSE_a0.5_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_bscheduler to 0.2	Strong:2, Moderate:1
CE_a1_bscheduler to 0.05_gscheduler to 0.2	5	4	9	0.56	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0	Moderate:2, Weak:2, Minimal:1	**9**	**0**	**9**	**1.00**	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_b0_gscheduler to 0.2, MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—	Strong:5, Weak:2, Moderate:1, Minimal:1
CE_a1_bscheduler to 0.05_g0	5	5	10	0.50	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.2,MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0	Moderate:4, Minimal:1	9	3	12	0.75	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_b0_gscheduler to 0.2, MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0	Moderate:3, Strong:3, Weak:3
MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	5	7	12	0.42	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Weak:3, Minimal:2	1	13	14	0.07	MSE_a0.5_bscheduler to 0.05_g0	CE_a0.5_b0_g0, CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Minimal:1
MSE_a0.5_b0_gscheduler to 0.2	6	4	10	0.40	CE_a0.5_b0_g0, CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2, MSE_a0.5_bscheduler to 0.05_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2, MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Minimal:2, Weak:2	10	1	11	0.91	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	MSE_a1_b0_g0	Strong:5, Moderate:2, Minimal:2, Weak:1
CE_a0.5_b0_gscheduler to 0.2	1	10	11	0.09	CE_a1_b0_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Weak:1	1	13	14	0.07	MSE_a0.5_bscheduler to 0.05_g0	CE_a0.5_b0_g0, CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Moderate:1

Table 31: Practical evidence assessment of loss ablations in the SSVEP task (Part 2 of 3). Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
CE_a0.5_b0_g0	1	11	12	0.08	CE_a1_b0_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_g0, MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Moderate:1	3	10	13	0.23	CE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0	Moderate:2, Strong:1
CE_a1_b0_gscheduler to 0.2	1	11	12	0.08	CE_a1_b0_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Weak:1	6	7	13	0.46	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_b0_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	CE_a1_b0_g0, CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2	Moderate:2, Strong:2, Minimal:1, Weak:1
MSE_a0.5_bscheduler to 0.05_g0	1	11	12	0.08	CE_a1_b0_g0	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	Weak:1	0	15	15	0.00	—	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—
CE_a1_b0_g0	0	15	15	0.00	—	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—	9	0	9	1.00	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2, CE_a1_b0_gscheduler to 0.2, MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0, MSE_a1_bscheduler to 0.05_gscheduler to 0.2	—	Strong:6, Moderate:2, Weak:1
MSE_a1_bscheduler to 0.05_gscheduler to 0.2	7	5	12	0.58	CE_a0.5_b0_g0, CE_a0.5_b0_gscheduler to 0.2,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2, MSE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0, CE_a0.5_bscheduler to 0.05_gscheduler to 0.2,MSE_a1_b0_g0, MSE_a1_b0_gscheduler to 0.2,MSE_a1_bscheduler to 0.05_g0	Weak:4, Minimal:2, Moderate:1	3	9	12	0.25	CE_a0.5_b0_gscheduler to 0.2,MSE_a0.5_bscheduler to 0.05_g0, MSE_a0.5_bscheduler to 0.05_gscheduler to 0.2	CE_a0.5_bscheduler to 0.05_g0,CE_a1_b0_g0, CE_a1_b0_gscheduler to 0.2,CE_a1_bscheduler to 0.05_g0,CE_a1_bscheduler to 0.05_gscheduler to 0.2,MSE_a0.5_b0_g0, MSE_a0.5_b0_gscheduler to 0.2,MSE_a1_b0_gscheduler to 0.2	Strong:2, Moderate:1

Table 32: Practical evidence assessment of loss ablations in the SSVEP task (Part 3 of 3). Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

Table 33

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
x + skips	4	0	4	1.00	skips, x + x_hat + skips, z + x, z only	—	Moderate:2, Weak:1, Minimal:1	1	3	4	0.25	skips	x_hat + skips, z + x_hat, z only	Weak:1
z + x_hat	5	0	5	1.00	skips, x + x_hat, x + x_hat + skips, z + x, z only	—	Minimal:3, Moderate:2	3	1	4	0.75	skips	x_hat + skips, x + skips, x + x_hat	Weak:2, Moderate:1
x_hat + skips	2	0	2	1.00	skips, x + x_hat + skips	—	Weak:1, Moderate:1	8	0	8	1.00	skips, x + skips, x + x_hat, x + x_hat + skips, z + skips, z + x, z + x_hat, z only	—	Strong:5, Moderate:2, Weak:1
z + skips	3	0	3	1.00	skips, x + x_hat + skips, z + x	—	Minimal:2, Moderate:1	1	1	2	0.50	skips	x_hat + skips	Strong:1
x + x_hat	3	1	4	0.75	skips, x + x_hat + skips, z + x	z + x_hat	Minimal:2, Moderate:1	1	3	4	0.25	skips	x_hat + skips, z + x_hat, z only	Moderate:1
z only	2	2	4	0.50	skips, x + x_hat + skips	x + skips, z + x_hat	Minimal:1, Moderate:1	3	1	4	0.75	skips	x_hat + skips, x + skips, x + x_hat	Moderate:2, Weak:1
z + x	1	4	5	0.20	skips	x + skips, x + x_hat, z + skips, z + x_hat	Moderate:1	1	1	2	0.50	skips	x_hat + skips	Strong:1
x + x_hat + skips	1	6	7	0.143	skips	x + skips, x + x_hat, x_hat + skips, z + skips, z + x_hat, z only	Minimal:1	1	1	2	0.50	skips	x_hat + skips	Weak:1
skips	0	8	8	0.00	—	x + skips, x + x_hat, x + x_hat + skips, x_hat + skips, z + skips, z + x, z + x_hat, z only	—	0	8	8	0.00	—	x + skips, x + x_hat, x + x_hat + skips, x_hat + skips, z + skips, z + x, z + x_hat, z only	—

Table 33: Practical evidence assessment of decoder input ablations in the P300 task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Table 34

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
eegnet_classifier__x	6	0	6	1.00	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat, fc_classifier__z	—	Strong:6	6	0	6	1.00	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat, fc_classifier__z	—	Strong:6
fc_classifier__z	4	1	5	0.80	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x	Strong:3, Weak:1	0	5	5	0.00	—	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	—
fc_classifier__decoder_out	4	1	5	0.80	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x	Strong:3, Moderate:1	5	1	6	0.83	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__x, fc_classifier__x_hat, fc_classifier__z	eegnet_classifier__x	Strong:2, Weak:2, Moderate:1
eegnet_classifier__decoder_out	3	3	6	0.50	eegnet_classifier__x_hat, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Weak:2, Strong:1	2	2	4	0.50	eegnet_classifier__x_hat, fc_classifier__z	eegnet_classifier__x, fc_classifier__decoder_out	Strong:2
fc_classifier__x	1	4	5	0.20	eegnet_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Strong:1	2	2	4	0.50	eegnet_classifier__x_hat, fc_classifier__z	eegnet_classifier__x, fc_classifier__decoder_out	Strong:2
fc_classifier__x_hat	1	4	5	0.20	eegnet_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Strong:1	2	2	4	0.50	eegnet_classifier__x_hat, fc_classifier__z	eegnet_classifier__x, fc_classifier__decoder_out	Strong:2
eegnet_classifier__x_hat	0	6	6	0.00	—	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat, fc_classifier__z	—	0	5	5	0.00	—	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	—

Table 34: Practical evidence assessment of classifier tpye ablations in the P300 task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
no_ddpm_x_no_decoder	2	0	2	1.00	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:2	2	1	3	0.67	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	use_ddpm_x_no_decoder	Strong:2
no_ddpm_x_use_decoder	2	0	2	1.00	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:2	2	1	3	0.67	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	use_ddpm_x_no_decoder	Strong:2
use_ddpm_x_no_decoder	**3**	0	3	**1.00**	use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:2 Minimal:1	**5**	0	5	**1.00**	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Moderate:2 Strong:2 Weak:1
use_ddpm_x_use_decoder	2	1	3	0.67	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	use_ddpm_x_no_decoder	Strong:2	2	1	3	0.67	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	use_ddpm_x_no_decoder	Strong:2
use_ddpm_x_hat_no_decoder	1	4	5	0.20	use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder	Moderate:1	0	5	5	0.00	—	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_hat_use_decoder	—
use_ddpm_x_hat_use_decoder	0	5	5	0.00	—	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder	—	1	4	5	0.20	use_ddpm_x_hat_no_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder	Moderate:1

Table 35: Practical evidence assessment of architecture ablations in the P300 task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
layer-1_randNo	6	0	6	1.00	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes	—	Moderate:4, Minimal:1, Weak:1	**11**	0	11	**1.00**	layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Strong:9, Minimal:2
layer-1_randYes	5	0	5	1.00	layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes	—	Moderate:3, Weak:2	**10**	1	11	**0.91**	layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	layer-1_randNo	Strong:9, Minimal:1
layer0_randNo	**9**	0	9	**1.00**	layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Weak:8, Minimal:1	9	2	11	0.82	layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	layer-1_randNo, layer-1_randYes	Strong:6, Moderate:2, Weak:1
layer0_randYes	**6**	1	7	**0.86**	layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randYes	layer0_randNo	Weak:5, Minimal:1	7	3	10	0.70	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo	Strong:4, Moderate:3
layer4_randNo	5	1	6	0.83	layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes	layer0_randNo	Weak:5	4	5	9	0.44	layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randYes	Moderate:3, Weak:1
layer1_randYes	5	2	7	0.71	layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes	layer-1_randNo, layer0_randNo	Moderate:5	0	11	11	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—

Table 36: Practical evidence assessment of mixup ablations in the P300 task (Part 1 of 2). Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
layer4_randYes	5	2	7	0.71	layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes	layer0_randNo, layer0_randYes	Moderate:3, Weak:2	7	3	10	0.70	layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo	Strong:5, Moderate:2
layer3_randYes	4	7	11	0.36	layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randYes, layer4_randNo, layer4_randYes	Weak:3, Minimal:1	1	5	6	0.17	layer1_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randYes	Weak:1
layer1_randNo	3	8	11	0.27	layer2_randNo, layer2_randYes, layer3_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randYes, layer3_randYes, layer4_randNo, layer4_randYes	Weak:2, Minimal:1	1	8	9	0.11	layer1_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer3_randNo, layer4_randNo, layer4_randYes	Moderate:1
layer2_randYes	1	9	10	0.10	layer2_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer3_randYes, layer4_randNo, layer4_randYes	Weak:1	4	5	9	0.44	layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer4_randYes	Moderate:1, Strong:1, Weak:1, Minimal:1
layer3_randNo	1	9	10	0.10	layer2_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer3_randYes, layer4_randNo, layer4_randYes	Minimal:1	2	7	9	0.22	layer1_randNo, layer1_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo, layer4_randYes	Weak:1, Moderate:1
layer2_randNo	0	11	11	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	1	7	8	0.13	layer1_randYes	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer2_randYes, layer4_randNo, layer4_randYes	Strong:1

Table 37: Practical evidence assessment of mixup ablations in the P300 task (Part 2 of 2). Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
x_hat + skips	2	4	6	0.333	x + x_hat + skips z + skips	x + skips z + x z + x_hat z only	Weak:2	**5**	0	5	**1.00**	skips x + skips x + x_hat x + x_hat + skips z + skips z + x z + x_hat z only	—	Strong:5 Moderate:2 Weak:1
x + x_hat + skips	1	6	7	0.143	z + skips	x + skips x + x_hat x_hat + skips z + x z + x_hat z only	Minimal:1	2	5	7	0.286	skips z + skips	x + skips x + x_hat x_hat + skips z + x z + x_hat	Weak:1 Moderate:1
x + skips	3	2	5	0.60	x + x_hat + skips x_hat + skips z + skips	z + x z only	Weak:2 Moderate:1	**5**	0	5	**1.00**	skips x + x_hat + skips z + skips z + x_hat z only	—	Strong:2 Weak:1 Minimal:1 Moderate:1
z + skips	0	8	8	0.00	—	skips x + skips x + x_hat x + x_hat + skips x_hat + skips z + x z + x_hat z only	—	0	7	7	0.00	—	x + skips x + x_hat x + x_hat + skips x_hat + skips z + x z + x_hat z only	—
x + x_hat	3	3	6	0.50	skips x + x_hat + skips z + skips	z + x z + x_hat z only	Weak:2 Strong:1	4	0	4	1.00	skips x + x_hat + skips z + skips z only	—	Strong:2 Weak:1 Moderate:1
z only	**7**	1	8	**0.875**	skips x + skips x + x_hat x + x_hat + skips x_hat + skips z + skips z + x_hat	z + x	Strong:4 Weak:3	2	4	6	0.333	skips z + skips	x + skips x + x_hat x_hat + skips z + x	Moderate:2
z + x_hat	5	2	7	0.714	skips x + x_hat x + x_hat + skips x_hat + skips z + skips	z + x z only	Strong:3 Weak:2	3	2	5	0.60	skips x + x_hat + skips z + skips	x + skips x_hat + skips	Strong:2 Weak:1
z + x	**8**	0	8	**1.00**	skips x + skips x + x_hat x + x_hat + skips x_hat + skips z + skips z + x_hat z only	—	Strong:5 Moderate:3	4	0	4	1.00	skips x + x_hat + skips z + skips z only	—	Weak:2 Strong:2
skips	1	4	5	0.20	z + skips	x + x_hat z + x z + x_hat z only	Strong:1	0	7	7	0.00	—	x + skips x + x_hat x + x_hat + skips x_hat + skips z + x z + x_hat z only	—

Table 38: Practical evidence assessment of decoder input ablations in the MI task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Table 39

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
eegnet_classifier__x	**6**	0	6	**1.00**	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat, fc_classifier__z	—	Strong:6	**6**	0	6	**1.00**	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat, fc_classifier__z	—	Strong:6
fc_classifier__z	**5**	1	6	**0.83**	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x	Strong:5	**5**	1	6	**0.83**	eegnet_classifier__decoder_out, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x	Strong:5
eegnet_classifier__decoder_out	4	2	6	0.67	eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x, fc_classifier__z	Strong:3 Moderate:1	4	2	6	0.67	eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__x, fc_classifier__z	Strong:3 Moderate:1
fc_classifier__decoder_out	3	3	6	0.50	eegnet_classifier__x_hat, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__z	Strong:3	3	3	6	0.50	eegnet_classifier__x_hat, fc_classifier__x, fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__z	Strong:3
fc_classifier__x	2	4	6	0.33	eegnet_classifier__x_hat, fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Strong:2	2	4	6	0.33	eegnet_classifier__x_hat, fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__z	Strong:2
eegnet_classifier__x_hat	1	5	6	0.17	fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__z	Strong:1	1	5	6	0.17	fc_classifier__x_hat	eegnet_classifier__decoder_out, eegnet_classifier__x, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__z	Strong:1
fc_classifier__x_hat	0	6	6	0.00	—	eegnet_classifier__decoder_out, eegnet_classifier__x, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__z	—	0	6	6	0.00	—	eegnet_classifier__decoder_out, eegnet_classifier__x, eegnet_classifier__x_hat, fc_classifier__decoder_out, fc_classifier__x, fc_classifier__z	—

Table 39: Practical evidence assessment of classifier type ablations in the MI task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Table 40

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
no_ddpm__x__use_decoder	**4**	0	4	**1.00**	no_ddpm__x__no_decoder, use_ddpm__x__no_decoder, use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	—	Strong:3 Moderate:1	2	3	5	0.40	use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	no_ddpm__x__no_decoder, use_ddpm__x__no_decoder, use_ddpm__x__use_decoder	Strong:2
use_ddpm__x__use_decoder	**4**	0	4	**1.00**	no_ddpm__x__no_decoder, use_ddpm__x__no_decoder, use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	—	Strong:4	3	1	4	0.75	no_ddpm__x__use_decoder, use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	use_ddpm__x__no_decoder	Strong:2 Weak:1
no_ddpm__x__no_decoder	2	2	4	0.50	use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	no_ddpm__x__use_decoder, use_ddpm__x__use_decoder	Strong:2	3	1	4	0.75	no_ddpm__x__use_decoder, use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	use_ddpm__x__no_decoder	Strong:3
use_ddpm__x__no_decoder	2	2	4	0.50	use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	no_ddpm__x__use_decoder, use_ddpm__x__use_decoder	Strong:2	**5**	0	5	**1.00**	no_ddpm__x__no_decoder, no_ddpm__x__use_decoder, use_ddpm__x__use_decoder, use_ddpm__x_hat__no_decoder, use_ddpm__x_hat__use_decoder	—	Strong:3 Weak:1 Moderate:1
use_ddpm__x_hat__no_decoder	1	4	5	0.20	use_ddpm__x_hat__use_decoder	no_ddpm__x__no_decoder, no_ddpm__x__use_decoder, use_ddpm__x__no_decoder, use_ddpm__x__use_decoder	Strong:1	0	4	4	0.00	—	no_ddpm__x__no_decoder, no_ddpm__x__use_decoder, use_ddpm__x__no_decoder, use_ddpm__x__use_decoder	—
use_ddpm__x_hat__use_decoder	0	5	5	0.00	—	no_ddpm__x__no_decoder, no_ddpm__x__use_decoder, use_ddpm__x__no_decoder, use_ddpm__x__use_decoder, use_ddpm__x_hat__no_decoder	—	0	4	4	0.00	—	no_ddpm__x__no_decoder, no_ddpm__x__use_decoder, use_ddpm__x__no_decoder, use_ddpm__x__use_decoder	—

Table 40: Practical evidence assessment of decoder input ablations in the MI task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
layer0_randYes	**10**	0	10	**1.00**	layer-1_randNo, layer-1_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Strong:7, Moderate:2, Minimal:1	**9**	0	9	**1.00**	layer-1_randNo, layer-1_randYes, layer0_randNo, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo, layer4_randNo, layer4_randYes	—	Weak:6, Moderate:2, Strong:1
layer0_randNo	**9**	0	9	**1.00**	layer-1_randNo, layer-1_randYes, layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Moderate:6, Strong:3	1	3	4	0.25	layer1_randNo	layer0_randYes, layer2_randYes, layer3_randYes	Weak:1
layer1_randYes	**9**	1	10	**0.90**	layer-1_randNo, layer-1_randYes, layer1_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	layer0_randYes	Strong:6, Moderate:3	3	3	6	0.50	layer-1_randYes, layer1_randNo, layer4_randNo	layer0_randYes, layer2_randYes, layer3_randYes	Weak:3
layer3_randYes	6	3	9	0.67	layer-1_randNo, layer-1_randYes, layer2_randNo, layer2_randYes, layer4_randNo, layer4_randYes	layer0_randNo, layer0_randYes, layer1_randYes	Moderate:3, Strong:2, Weak:1	**8**	0	8	**1.00**	layer-1_randNo, layer-1_randYes, layer0_randNo, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo, layer4_randNo	—	Weak:4, Moderate:4
layer3_randNo	5	3	8	0.63	layer-1_randNo, layer-1_randYes, layer2_randYes, layer4_randNo, layer4_randYes	layer0_randNo, layer0_randYes, layer1_randYes	Weak:3, Moderate:2	2	3	5	0.40	layer-1_randNo, layer1_randNo	layer0_randYes, layer2_randYes, layer3_randYes	Minimal:1, Weak:1
layer1_randNo	4	3	7	0.57	layer-1_randNo, layer2_randYes, layer4_randNo, layer4_randYes	layer0_randNo, layer0_randYes, layer1_randYes	Moderate:2, Weak:1, Minimal:1	0	9	9	0.00	—	layer-1_randNo, layer0_randNo, layer0_randYes, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randYes	—
layer2_randNo	3	4	7	0.43	layer-1_randNo, layer2_randYes, layer4_randNo	layer0_randNo, layer0_randYes, layer1_randYes, layer3_randYes	Weak:1, Minimal:1, Moderate:1	3	3	6	0.50	layer-1_randNo, layer-1_randYes, layer1_randNo	layer0_randYes, layer2_randYes, layer3_randYes	Moderate:2, Minimal:1
layer-1_randYes	1	5	6	0.17	layer-1_randNo	layer0_randYes, layer0_randYes, layer1_randYes, layer3_randNo, layer3_randYes	Weak:1	0	8	8	0.00	—	layer-1_randNo, layer0_randYes, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randYes	—
layer2_randYes	1	7	8	0.13	layer4_randNo	layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo, layer3_randYes	Weak:1	**8**	0	8	**1.00**	layer-1_randNo, layer-1_randYes, layer0_randNo, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo, layer4_randYes	—	Weak:4, Strong:2, Moderate:1, Minimal:1
layer-1_randNo	0	8	8	0.00	—	layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo, layer3_randYes	—	**2**	4	6	**0.33**	layer-1_randYes, layer1_randNo	layer0_randYes, layer2_randNo, layer2_randYes, layer3_randYes	Weak:1, Moderate:1
layer4_randNo	0	8	8	0.00	—	layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes	—	0	3	3	0.00	—	layer0_randYes, layer1_randYes, layer3_randYes	—
layer4_randYes	0	6	6	0.00	—	layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer3_randNo, layer3_randYes	—	**2**	2	4	**0.50**	layer-1_randYes, layer1_randNo	layer0_randYes, layer2_randYes	Weak:2

Table 41: Practical evidence assessment of architecture ablations in the imagined speech task. Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
x + x_hat	**5**	0	5	**1.00**	skips x + skips z + skips z + x z only	—	Moderate:3 Strong:1 Weak:1	1	7	8	0.125	z + skips	skips x + skips x + x_hat + skips x_hat + skips z + x z + x_hat z only	Weak:1
z + x	**5**	1	6	**0.833**	x + skips x + x_hat + skips x_hat + skips z + x_hat z only	x + x_hat	Weak:4 Strong:1	4	0	4	1.00	skips x + x_hat + skips z + skips z only	—	Weak:2 Strong:2
z + skips	4	1	5	0.800	x + skips x + x_hat + skips x_hat + skips z only	x + x_hat	Weak:2 Moderate:2	0	7	7	0.000	—	skips x + skips x + x_hat x + x_hat + skips x_hat + skips z + x z + x_hat z only	—
skips	3	1	4	0.750	x + skips x + x_hat + skips z only	x + x_hat	Weak:2 Moderate:1	3	5	8	0.375	x + x_hat z + skips z + x	x + skips x + x_hat + skips x_hat + skips z + x_hat z only	Weak:3
z + x_hat	3	1	4	0.750	x + x_hat + skips x_hat + skips z only	z + x	Weak:2 Strong:1	**8**	0	8	1.00	skips x + skips x + x_hat x + x_hat + skips x_hat + skips z + skips z + x z only	—	Weak:4 Moderate:3 Strong:1
x_hat + skips	1	3	4	0.250	z only	z + skips z + x z + x_hat	Strong:1	**6**	1	7	**0.857**	skips x + skips x + x_hat z + skips z + x z only	z + x_hat	Weak:3 Moderate:2 Strong:1
x + skips	1	4	5	0.200	z only	skips x + x_hat z + skips z + x	Moderate:1	3	3	6	0.500	skips x + x_hat z + skips	x + x_hat + skips x_hat + skips z + x_hat	Weak:1 Strong:1 Moderate:1
x + x_hat + skips	1	4	5	0.200	z only	skips z + skips z + x z + x_hat	Moderate:1	**6**	1	7	**0.857**	skips x + skips x + x_hat z + skips z + x z only	z + x_hat	Weak:3 Moderate:2 Strong:1
z only	0	8	8	0.00	—	skips x + skips x + x_hat x + x_hat + skips x_hat + skips z + skips z + x z + x_hat	—	4	3	7	0.571	skips x + x_hat z + skips z + x	x + x_hat + skips x_hat + skips z + x_hat	Weak:3 Moderate:1

Table 42: Practical evidence assessment of decoder input ablations in the imagined speech task. Practical evidence assessment of mixup ablations in the MI task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
fc_classifier_decoder_out	**6**	0	6	**1.00**	eegnet_classifier_decoder_out eegnet_classifier_x eegnet_classifier_x_hat fc_classifier_x fc_classifier_x_hat fc_classifier_z	—	Strong:3 Moderate:3	1	4	5	0.20	eegnet_classifier_x_hat	eegnet_classifier_decoder_out eegnet_classifier_x fc_classifier_x_hat fc_classifier_z	Weak:1
fc_classifier_x	**4**	1	5	**0.80**	eegnet_classifier_x eegnet_classifier_x_hat fc_classifier_x_hat fc_classifier_z	fc_classifier_decoder_out	Strong:3 Weak:1	0	4	4	0.00	—	eegnet_classifier_decoder_out eegnet_classifier_x fc_classifier_x_hat fc_classifier_z	—
eegnet_classifier_decoder_out	4	1	5	**0.80**	eegnet_classifier_x eegnet_classifier_x_hat fc_classifier_x_hat fc_classifier_z	fc_classifier_decoder_out	Strong:3 Moderate:1	**4**	1	5	**0.80**	eegnet_classifier_x_hat fc_classifier_decoder_out fc_classifier_x fc_classifier_x_hat	fc_classifier_z	Moderate:3 Strong:1
fc_classifier_z	3	3	6	0.50	eegnet_classifier_x eegnet_classifier_x_hat fc_classifier_x_hat	eegnet_classifier_decoder_out fc_classifier_decoder_out fc_classifier_x	Strong:3	**6**	0	6	**1.00**	eegnet_classifier_decoder_out eegnet_classifier_x eegnet_classifier_x_hat fc_classifier_decoder_out fc_classifier_x fc_classifier_x_hat	—	Strong:3 Moderate:2 Weak:1
eegnet_classifier_x	2	4	6	0.33	eegnet_classifier_x_hat fc_classifier_x_hat	eegnet_classifier_decoder_out fc_classifier_decoder_out fc_classifier_x fc_classifier_z	Weak:2	**4**	1	5	**0.80**	eegnet_classifier_x_hat fc_classifier_decoder_out fc_classifier_x fc_classifier_x_hat	fc_classifier_z	Strong:2 Moderate:2
fc_classifier_x_hat	1	5	6	0.17	eegnet_classifier_x_hat	eegnet_classifier_decoder_out eegnet_classifier_x fc_classifier_decoder_out fc_classifier_x fc_classifier_z	Weak:1	3	3	6	0.50	eegnet_classifier_x_hat fc_classifier_decoder_out fc_classifier_x	eegnet_classifier_decoder_out eegnet_classifier_x fc_classifier_z	Weak:2 Strong:1
eegnet_classifier_x_hat	0	6	6	0.00	—	eegnet_classifier_decoder_out eegnet_classifier_x fc_classifier_decoder_out fc_classifier_x fc_classifier_x_hat fc_classifier_z	—	0	5	5	0.00	—	eegnet_classifier_decoder_out eegnet_classifier_x fc_classifier_decoder_out fc_classifier_x_hat fc_classifier_z	—

Table 43: Practical evidence assessment of classifier type ablations in the imagined speech task. Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
no_ddpm_x_no_decoder	4	0	4	1.00	use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:3 Weak:1	3	2	5	0.60	use_ddpm_x_no_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_use_decoder use_ddpm_x_use_decoder	Moderate:3
no_ddpm_x_use_decoder	3	0	3	1.00	use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:2 Moderate:1	5	0	5	1.00	no_ddpm_x_no_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	—	Strong:4 Moderate:1
use_ddpm_x_no_decoder	3	1	4	0.75	use_ddpm_x_use_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder	Strong:3	2	2	4	0.50	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder	Weak:1 Moderate:1
use_ddpm_x_use_decoder	2	3	5	0.40	use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder	Strong:2	3	1	4	0.75	no_ddpm_x_no_decoder use_ddpm_x_hat_no_decoder use_ddpm_x_hat_use_decoder	no_ddpm_x_use_decoder	Moderate:2 Weak:1
use_ddpm_x_hat_no_decoder	0	4	4	0.00	—	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder	—	0	5	5	0.00	—	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder use_ddpm_x_hat_use_decoder	—
use_ddpm_x_hat_use_decoder	0	4	4	0.00	—	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder	—	1	4	5	0.20	use_ddpm_x_hat_no_decoder	no_ddpm_x_no_decoder no_ddpm_x_use_decoder use_ddpm_x_no_decoder use_ddpm_x_use_decoder	Weak:1

Each configuration's wins, losses, total comparisons, and win rate are reported, along with the corresponding lists of winning and losing opponents and an evidence summary.

Config	Seen							Unseen						
	Wins	Losses	Total	Rate	Win List	Loss List	Evidence	Wins	Losses	Total	Rate	Win List	Loss List	Evidence
layer0_randYes	**11**	0	11	**1.00**	layer-1_randNo, layer-1_randYes, layer0_randNo, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo, layer4_randYes	—	Strong:11	**5**	2	7	**0.71**	layer-1_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo	layer-1_randNo, layer2_randYes	Strong:3, Weak:2
layer1_randNo	**7**	1	8	**0.88**	layer-1_randNo, layer-1_randYes, layer0_randNo, layer2_randYes, layer3_randNo, layer4_randNo, layer4_randYes	layer0_randYes	Weak:6, Moderate:1	4	6	10	0.40	layer-1_randYes, layer1_randYes, layer2_randNo, layer3_randNo	layer-1_randNo, layer0_randYes, layer2_randYes, layer3_randYes, layer4_randNo, layer4_randYes	Weak:2, Strong:1, Moderate:1
layer1_randYes	6	1	7	0.86	layer0_randNo, layer2_randNo, layer2_randYes, layer3_randNo, layer3_randYes, layer4_randNo	layer0_randYes	Moderate:6	1	3	4	0.25	layer3_randNo	layer0_randYes, layer1_randNo, layer2_randYes	Moderate:1
layer2_randNo	3	2	5	0.60	layer0_randNo, layer2_randYes, layer4_randNo	layer0_randYes, layer1_randYes	Moderate:2, Weak:1	1	9	10	0.10	layer3_randNo	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer2_randYes, layer3_randYes, layer4_randNo, layer4_randYes	Strong:1
layer3_randNo	4	3	7	0.57	layer0_randNo, layer2_randYes, layer3_randYes, layer4_randNo	layer0_randYes, layer1_randNo, layer1_randYes	Moderate:2, Weak:1, Strong:1	0	11	11	0.00	—	layer-1_randNo, layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer2_randYes, layer3_randYes, layer4_randNo, layer4_randYes	—
layer-1_randNo	1	2	3	0.33	layer4_randNo	layer0_randYes, layer1_randNo	Moderate:1	**6**	0	6	**1.00**	layer-1_randYes, layer0_randNo, layer0_randYes, layer1_randNo, layer2_randNo, layer3_randNo	—	Moderate:3, Weak:2, Strong:1
layer0_randNo	1	5	6	0.17	layer4_randNo	layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo	Moderate:1	3	1	4	0.75	layer-1_randYes, layer2_randNo, layer3_randNo	layer-1_randNo	Moderate:2, Strong:1
layer-1_randYes	0	2	2	0.00	—	layer0_randYes, layer1_randNo	—	2	4	6	0.33	layer2_randNo, layer3_randNo	layer-1_randNo, layer0_randNo, layer0_randYes, layer1_randNo	Moderate:1, Strong:1
layer2_randYes	0	5	5	0.00	—	layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo	—	5	0	5	1.00	layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo	—	Moderate:3, Weak:1, Strong:1
layer3_randYes	0	3	3	0.00	—	layer0_randYes, layer1_randYes, layer3_randNo	—	3	0	3	1.00	layer1_randNo, layer2_randNo, layer3_randNo	—	Weak:1, Moderate:1, Strong:1
layer4_randNo	0	7	7	0.00	—	layer-1_randNo, layer0_randNo, layer0_randYes, layer1_randNo, layer1_randYes, layer2_randNo, layer3_randNo	—	3	0	3	1.00	layer1_randNo, layer2_randNo, layer3_randNo	—	Weak:1, Moderate:1, Strong:1
layer4_randYes	0	2	2	0.00	—	layer0_randYes, layer1_randNo	—	3	0	3	1.00	layer1_randNo, layer2_randNo, layer3_randNo	—	Weak:1, Moderate:1, Strong:1

Table 44: Practical evidence assessment of mixup ablations in the imagined speech task. Each row shows win/loss stats and qualitative evidence for seen and unseen subject comparisons.

config_1	config_2	mean_diff	p_left	p_rope	p_right	n_seeds
x + x_hat + skips	x + x_hat	0.006993006993	0.4072213877	0.4576239803	0.135154632	3
x + x_hat + skips	x_hat + skips	0.001554001554	0.1277370191	0.7904370663	0.08182591465	3
x + x_hat + skips	x + skips	0.002331002331	0.05622746549	0.9195907337	0.02418180077	3
x + x_hat + skips	skips	0.01825951826	0.6552695743	0.2173670696	0.1273633562	3
x + x_hat + skips	z only	0.00777000777	0.4601924043	0.3082698215	0.2315377742	3
x + x_hat + skips	z + x	0.009712509713	0.4872757353	0.4465708069	0.06615345775	3
x + x_hat + skips	z + x_hat	0.006993006993	0.291618297	0.6748438492	0.03353785374	3
x + x_hat + skips	z + skips	0.005439005439	0.3449252349	0.5256993868	0.1293753783	3
x + x_hat	x_hat + skips	-0.005439005439	0.165056371	0.463719159	0.37122447	3
x + x_hat	x + skips	-0.004662004662	0.1867724085	0.4536427293	0.3595848622	3
x + x_hat	skips	0.01126651127	0.5451105314	0.3726927806	0.08219668798	3
x + x_hat	z only	0.000777000777	0.2351467355	0.5595924463	0.2052608182	3
x + x_hat	z + x	0.00271950272	0.1342152618	0.8069448934	0.05883984476	3
x + x_hat	z + x_hat	3.70E-17	0.2621371795	0.475725641	0.2621371795	3
x + x_hat	z + skips	-0.001554001554	0.2788090622	0.3907941262	0.3303968116	3
x_hat + skips	x + skips	0.000777000777	0.057196689	0.8989675316	0.0438357794	3
x_hat + skips	skips	0.01670551671	0.6462311243	0.2402124945	0.1135563811	3
x_hat + skips	z only	0.006216006216	0.4259897872	0.3439535126	0.2300567002	3
x_hat + skips	z + x	0.008158508159	0.4138874767	0.5186213571	0.06749116622	3
x_hat + skips	z + x_hat	0.005439005439	0.05348962787	0.9410602535	0.005450118599	3
x_hat + skips	z + skips	0.003885003885	0.1739873248	0.7710487483	0.05496392697	3
x + skips	skips	0.01592851593	0.6128314643	0.2430106582	0.1441578775	3
x + skips	z only	0.005439005439	0.4213678234	0.3158824392	0.2627497374	3
x + skips	z + x	0.007381507382	0.3977108733	0.5079004852	0.09438864146	3
x + skips	z + x_hat	0.004662004662	0.0644456337	0.9253444009	0.01020996542	3
x + skips	z + skips	0.003108003108	0.2208576006	0.673134884	0.1060075154	3
skips	z only	-0.01048951049	0.009178275343	0.4297996164	0.5610221082	3
skips	z + x	-0.008547008547	0.1032182657	0.4476016877	0.4491800465	3
skips	z + x_hat	-0.01126651127	0.1694595733	0.304340691	0.5261997357	3
skips	z + skips	-0.01282051282	0.1632223436	0.2808168648	0.5559607915	3
z only	z + x	0.001942501943	0.2821134095	0.5093980036	0.208488587	3
z only	z + x_hat	-0.000777000777	0.3171595098	0.3421932156	0.3406472746	3
z only	z + skips	-0.002331002331	0.3033447828	0.3252097791	0.3714454381	3
z + x	z + x_hat	-0.00271950272	0.1386152854	0.618199462	0.2431852526	3
z + x	z + skips	-0.004273504274	0.1744886081	0.4881975089	0.337313883	3
z + x_hat	z + skips	-0.001554001554	0.0793232897	0.7962580914	0.1244186189	3

Table 45: Bayesian evidence assessment of decoder input ablations on seen subjects in the SSVEP task

config_1	config_2	mean_diff	p_left	p_rope	p_right	n_seeds
x + x_hat + skips	x + x_hat	-0.01282051282	0.0491903225	0.3260644706	0.6247452069	3
x + x_hat + skips	x_hat + skips	-0.004273504274	0.1753950877	0.4865895812	0.3380153311	3
x + x_hat + skips	x + skips	0.01388888889	0.7620140193	0.2213532638	0.01663271685	3
x + x_hat + skips	skips	0.005341880342	0.4343899953	0.265424077	0.3001859277	3
x + x_hat + skips	z only	-0.01602564103	0.1639164971	0.233235663	0.6028478399	3
x + x_hat + skips	z + x	0.01068376068	0.5356858485	0.4182145309	0.04609962059	3
x + x_hat + skips	z + x_hat	0.005341880342	0.4334799737	0.2686965897	0.2978234365	3
x + x_hat + skips	z + skips	-0.004273504274	0.2210581421	0.4091356847	0.3698061732	3
x + x_hat	x_hat + skips	0.008547008547	0.4736673258	0.3055536853	0.2207789889	3
x + x_hat	x + skips	0.02670940171	0.8481200192	0.1045169345	0.04736304634	3
x + x_hat	skips	0.01816239316	0.6595313467	0.2193905632	0.1210780901	3
x + x_hat	z only	-0.003205128205	0.2513575889	0.3900876037	0.3585548074	3
x + x_hat	z + x	0.0235042735	0.9215492218	0.06270373278	0.01574704541	3
x + x_hat	z + x_hat	0.01816239316	0.5995193453	0.1874197081	0.2130609465	3
x + x_hat	z + skips	0.008547008547	0.4309028719	0.5050801286	0.06401699946	3
x_hat + skips	x + skips	0.01816239316	0.8084563537	0.1605116455	0.03103200074	3
x_hat + skips	skips	0.009615384615	0.496279061	0.1811444739	0.3225764651	3
x_hat + skips	z only	-0.01175213675	0.2745850211	0.2050900957	0.5203248832	3
x_hat + skips	z + x	0.01495726496	0.5974712829	0.256193859	0.1463348581	3
x_hat + skips	z + x_hat	0.009615384615	0.4945607409	0.248020708	0.2574185511	3
x_hat + skips	z + skips	0	0.3725136154	0.2549727692	0.3725136154	3
x + skips	skips	-0.008547008547	0.2957714672	0.2217461067	0.4824824261	3
x + skips	z only	-0.02991452991	0.1179607274	0.1276686708	0.7543706018	3
x + skips	z + x	-0.003205128205	0.1686075062	0.5386346688	0.292757825	3
x + skips	z + x_hat	-0.008547008547	0.2589232622	0.2626141784	0.4784625594	3
x + skips	z + skips	-0.01816239316	0.1425873074	0.2153816627	0.6420310299	3
skips	z only	-0.02136752137	0.1243311617	0.1849632848	0.6907055535	3
skips	z + x	0.005341880342	0.4231177869	0.3049383138	0.2719438993	3
skips	z + x_hat	-3.70E-17	0.4155708997	0.1688582007	0.4155708997	3
skips	z + skips	-0.009615384615	0.09629904233	0.4171125382	0.4865884194	3
z only	z + x	0.02670940171	0.8291035932	0.1143919903	0.05650441656	3
z only	z + x_hat	0.02136752137	0.6598087955	0.1808495094	0.159341695	3
z only	z + skips	0.01175213675	0.5446226142	0.3272150548	0.1281623311	3
z + x	z + x_hat	-0.005341880342	0.281641804	0.2912679113	0.4270902847	3
z + x	z + skips	-0.01495726496	0.0765139553	0.2726360719	0.6508499728	3
z + x_hat	z + skips	-0.009615384615	0.3021151679	0.202109754	0.4957750781	3

Table 46: Bayesian evidence assessment of decoder input ablations on unseen subjects in the SSVEP task

config_1	config_2	mean_diff	p_left	p_rope	p_right	n_seeds
eegnet_classifier__x	eegnet_classifier__x_hat	0.7855477855	0.9974747527	0.0001244714922	0.002400775803	3
eegnet_classifier__x	eegnet_classifier__decoder_out	0.08935508936	0.9978271584	0.0007834572033	0.001389384359	3
eegnet_classifier__x	fc_classifier__x	0.7843822844	0.9996831675	1.57E-05	0.0003010938821	3
eegnet_classifier__x	fc_classifier__x_hat	0.8543123543	0.999946812	2.43E-06	5.08E-05	3
eegnet_classifier__x	fc_classifier__decoder_out	0.1153846154	0.9850522476	0.004248642321	0.0106991101	3
eegnet_classifier__x	fc_classifier__z	0.04079254079	0.9479425423	0.0308853512	0.02117210646	3
eegnet_classifier__x_hat	eegnet_classifier__decoder_out	-0.6961926962	0.003419689093	0.0002000567375	0.9963802542	3
eegnet_classifier__x_hat	fc_classifier__x	-0.001165501166	0.3978407016	0.1836293954	0.4185299031	3
eegnet_classifier__x_hat	fc_classifier__x_hat	0.06876456876	0.8055549637	0.05399336546	0.1404516708	3
eegnet_classifier__x_hat	fc_classifier__decoder_out	-0.6701631702	0.005419803428	0.0003276395382	0.994252557	3
eegnet_classifier__x_hat	fc_classifier__z	-0.7447552448	0.002980693126	0.0001629291043	0.9968563778	3
eegnet_classifier__decoder_out	fc_classifier__x	0.695027195	0.9995034081	2.77E-05	0.0004688562281	3
eegnet_classifier__decoder_out	fc_classifier__x_hat	0.764957265	0.9998358972	8.36E-06	0.0001557457272	3
eegnet_classifier__decoder_out	fc_classifier__decoder_out	0.02602952603	0.7551509035	0.1448922333	0.09995686318	3
eegnet_classifier__decoder_out	fc_classifier__z	-0.04856254856	0.00604968638	0.007581437855	0.9863688758	3
fc_classifier__x	fc_classifier__x_hat	0.06993006993	0.9425081197	0.02261977183	0.03487210851	3
fc_classifier__x	fc_classifier__decoder_out	-0.668997669	0.001548222681	9.49E-05	0.9983568467	3
fc_classifier__x	fc_classifier__z	-0.7435897436	0.0003773041956	2.08E-05	0.9996018672	3
fc_classifier__x_hat	fc_classifier__decoder_out	-0.7389277389	0.0002752569251	1.53E-05	0.9997094444	3
fc_classifier__x_hat	fc_classifier__z	-0.8135198135	0.0002801819742	1.41E-05	0.9997057092	3
fc_classifier__decoder_out	fc_classifier__z	-0.07459207459	0.03847802095	0.02264037834	0.9388816007	3

Table 47: Bayesian evidence assessment of classifier type ablations on seen subjects in the SSVEP task

config_1	config_2	mean_diff	p_left	p_rope	p_right	n_seeds
eegnet_classifier__x	eegnet_classifier__x_hat	0.719017094	0.9941250768	0.0003126409919	0.005562282177	3
eegnet_classifier__x	eegnet_classifier__decoder_out	0.1047008547	0.8517898021	0.03221550818	0.1159946897	3
eegnet_classifier__x	fc_classifier__x	0.6965811966	0.9941798993	0.0003194766474	0.005500624028	3
eegnet_classifier__x	fc_classifier__x_hat	0.7702991453	0.9919474317	0.0003981951421	0.007654373153	3
eegnet_classifier__x	fc_classifier__decoder_out	0.1153846154	0.9031687756	0.02244695533	0.0743842691	3
eegnet_classifier__x	fc_classifier__z	-0.03632478632	0.1578538502	0.1068760593	0.7352700904	3
eegnet_classifier__x_hat	eegnet_classifier__decoder_out	-0.6143162393	0.0003327796059	2.24E-05	0.9996448529	3
eegnet_classifier__x_hat	fc_classifier__x	-0.02243589744	0.1644621354	0.171609785	0.6639280796	3
eegnet_classifier__x_hat	fc_classifier__x_hat	0.05128205128	0.6739337523	0.06729475814	0.2587714896	3
eegnet_classifier__x_hat	fc_classifier__decoder_out	-0.6036324786	0.000797597804	5.45E-05	0.9991478929	3
eegnet_classifier__x_hat	fc_classifier__z	-0.7553418803	0.00335896058	0.0001807472277	0.9964602922	3
eegnet_classifier__decoder_out	fc_classifier__x	0.5918803419	0.9997431462	1.68E-05	0.000240079429	3
eegnet_classifier__decoder_out	fc_classifier__x_hat	0.6655982906	0.9951195884	0.0002807606336	0.004599650926	3
eegnet_classifier__decoder_out	fc_classifier__decoder_out	0.01068376068	0.5183108555	0.3529521795	0.1287369649	3
eegnet_classifier__decoder_out	fc_classifier__z	-0.141025641	0.04449883101	0.01221778853	0.9432833805	3
fc_classifier__x	fc_classifier__x_hat	0.07371794872	0.8224598002	0.0488305597	0.1287096401	3
fc_classifier__x	fc_classifier__decoder_out	-0.5811965812	0.0007981961578	5.67E-05	0.9991450746	3
fc_classifier__x	fc_classifier__z	-0.7329059829	0.002228941662	0.0001241570405	0.9976469013	3
fc_classifier__x_hat	fc_classifier__decoder_out	-0.6549145299	0.005394449501	0.0003339544716	0.994271596	3
fc_classifier__x_hat	fc_classifier__z	-0.8066239316	0.002928727096	0.0001475315086	0.9969237414	3
fc_classifier__decoder_out	fc_classifier__z	-0.1517094017	0.02672121585	0.007268100357	0.9660106838	3

Table 48: Bayesian evidence assessment of classifier variants on unseen subjects in the SSVEP task

config_1	config_2	mean_diff	p_left	p_rope	p_right	n_seeds
use_ddpm__x__use_decoder	use_ddpm__x__no_decoder	-0.004273504274	0.1467848185	0.539083023	0.3141321585	3
use_ddpm__x__use_decoder	use_ddpm__x_hat__use_decoder	0.7855477855	0.9999548373	2.24E-06	4.29E-05	3
use_ddpm__x__use_decoder	use_ddpm__x_hat__no_decoder	0.7836052836	0.999244801	3.75E-05	0.0007176953454	3
use_ddpm__x__use_decoder	no_ddpm__x__use_decoder	-0.05205905206	0.03269113195	0.03133239227	0.9359764758	3
use_ddpm__x__use_decoder	no_ddpm__x__no_decoder	-0.05866355866	0.05146770661	0.03796571886	0.9105665745	3
use_ddpm__x__no_decoder	use_ddpm__x_hat__use_decoder	0.7898212898	0.9999754926	1.21E-06	2.33E-05	3
use_ddpm__x__no_decoder	use_ddpm__x_hat__no_decoder	0.7878787879	0.9996523997	1.72E-05	0.0003304095815	3
use_ddpm__x__no_decoder	no_ddpm__x__use_decoder	-0.04778554779	0.008104232996	0.01025732533	0.9816384417	3
use_ddpm__x__no_decoder	no_ddpm__x__no_decoder	-0.05439005439	0.02293724067	0.02198948784	0.9550732715	3
use_ddpm__x_hat__use_decoder	use_ddpm__x_hat__no_decoder	-0.001942501943	0.3284789163	0.2911427916	0.380378292	3
use_ddpm__x_hat__use_decoder	no_ddpm__x__use_decoder	-0.8376068376	0.0001152440137	5.64E-06	0.9998791207	3
use_ddpm__x_hat__use_decoder	no_ddpm__x__no_decoder	-0.8442113442	0.0001994892911	9.67E-06	0.9997908367	3
use_ddpm__x_hat__no_decoder	no_ddpm__x__use_decoder	-0.8356643357	0.0002238272147	1.10E-05	0.9997652057	3
use_ddpm__x_hat__no_decoder	no_ddpm__x__no_decoder	-0.8422688423	2.68E-05	1.30E-06	0.9999719478	3
no_ddpm__x__use_decoder	no_ddpm__x__no_decoder	-0.006604506605	0.1552197591	0.4403376075	0.4044426334	3

Table 49: Bayesian evidence assessment of architecture ablations on seen subjects in the SSVEP task

config_1	config_2	mean_diff	p_left	p_rope	p_right	n_seeds
use_ddpm__x__use_decoder	use_ddpm__x__no_decoder	0.01175213675	0.5725664853	0.3657018961	0.06173161858	3
use_ddpm__x__use_decoder	use_ddpm__x_hat__use_decoder	0.7713675214	0.9975348705	0.0001237069014	0.002341422619	3
use_ddpm__x__use_decoder	use_ddpm__x_hat__no_decoder	0.7767094017	0.996752828	0.0001614971039	0.003085674931	3
use_ddpm__x__use_decoder	no_ddpm__x__use_decoder	-0.002136752137	0.3462081736	0.2562844925	0.3975073338	3
use_ddpm__x__use_decoder	no_ddpm__x__no_decoder	-0.008547008547	0.01580831276	0.6296662858	0.3545254015	3
use_ddpm__x__no_decoder	use_ddpm__x_hat__use_decoder	0.7596153846	0.9976326959	0.0001206223479	0.002246681788	3
use_ddpm__x__no_decoder	use_ddpm__x_hat__no_decoder	0.764957265	0.9969466315	0.0001542178536	0.002899150601	3
use_ddpm__x__no_decoder	no_ddpm__x__use_decoder	-0.01388888889	0.2474675827	0.2051155102	0.5474169071	3
use_ddpm__x__no_decoder	no_ddpm__x__no_decoder	-0.0202991453	0.02714667705	0.1212528557	0.8516004673	3
use_ddpm__x_hat__use_decoder	use_ddpm__x_hat__no_decoder	0.005341880342	0.347373062	0.5156378604	0.1369890776	3
use_ddpm__x_hat__use_decoder	no_ddpm__x__use_decoder	-0.7735042735	0.005124050777	0.0002675815198	0.9946083677	3
use_ddpm__x_hat__use_decoder	no_ddpm__x__no_decoder	-0.7799145299	0.002494230703	0.0001302361551	0.9973755331	3
use_ddpm__x_hat__no_decoder	no_ddpm__x__use_decoder	-0.7788461538	0.006097907255	0.0003152188219	0.9935868739	3
use_ddpm__x_hat__no_decoder	no_ddpm__x__no_decoder	-0.7852564103	0.003223991823	0.0001667800573	0.9966092281	3
no_ddpm__x__use_decoder	no_ddpm__x__no_decoder	-0.00641025641	0.281984361	0.2707144165	0.4473012224	3

Table 50: Bayesian evidence assessment of architecture ablations for unSeen subjects in the SSVEP task

config_1	config_2	mean_diff	p_left	p_rope	p_right	n_seeds
eegnet_classifier__x	eegnet_classifier__x_hat	0.719017094	0.9941250768	0.0003126409919	0.005562282177	3
eegnet_classifier__x	eegnet_classifier__decoder_out	0.1047008547	0.8517898021	0.03221550818	0.1159946897	3
eegnet_classifier__x	fc_classifier__x	0.6965811966	0.9941798993	0.0003194766474	0.005500624028	3
eegnet_classifier__x	fc_classifier__x_hat	0.7702991453	0.9919474317	0.0003981951421	0.007654373153	3
eegnet_classifier__x	fc_classifier__decoder_out	0.1153846154	0.9031687756	0.02244695533	0.0743842691	3
eegnet_classifier__x	fc_classifier__z	-0.03632478632	0.1578538502	0.1068760593	0.7352700904	3
eegnet_classifier__x_hat	eegnet_classifier__decoder_out	-0.6143162393	0.0003327796059	2.24E-05	0.9996448529	3
eegnet_classifier__x_hat	fc_classifier__x	-0.02243589744	0.1644621354	0.171609785	0.6639280796	3
eegnet_classifier__x_hat	fc_classifier__x_hat	0.05128205128	0.6739337523	0.06729475814	0.2587714896	3
eegnet_classifier__x_hat	fc_classifier__decoder_out	-0.6036324786	0.000797597804	5.45E-05	0.9991478929	3
eegnet_classifier__x_hat	fc_classifier__z	-0.7553418803	0.00335896058	0.0001807472277	0.9964602922	3
eegnet_classifier__decoder_out	fc_classifier__x	0.5918803419	0.9997431462	1.68E-05	0.000240079429	3
eegnet_classifier__decoder_out	fc_classifier__x_hat	0.6655982906	0.9951195884	0.0002807606336	0.004599650926	3
eegnet_classifier__decoder_out	fc_classifier__decoder_out	0.01068376068	0.5183108555	0.3529521795	0.1287369649	3
eegnet_classifier__decoder_out	fc_classifier__z	-0.141025641	0.04449883101	0.01221778853	0.9432833805	3
fc_classifier__x	fc_classifier__x_hat	0.07371794872	0.8224598002	0.0488305597	0.1287096401	3
fc_classifier__x	fc_classifier__decoder_out	-0.5811965812	0.0007981961578	5.67E-05	0.9991450746	3
fc_classifier__x	fc_classifier__z	-0.7329059829	0.002228941662	0.0001241570405	0.9976469013	3
fc_classifier__x_hat	fc_classifier__decoder_out	-0.6549145299	0.005394449501	0.0003339544716	0.994271596	3
fc_classifier__x_hat	fc_classifier__z	-0.8066239316	0.002928727096	0.0001475315086	0.9969237414	3
fc_classifier__decoder_out	fc_classifier__z	-0.1517094017	0.02672121585	0.007268100357	0.9660106838	3

Table 51: Bayesian evidence assessment of classifier type ablations on unseen subjects in the SSVEP task

config_1	config_2	mean_diff	p_value	mean_1	mean_2	n_seeds
x + x_hat + skips	x + x_hat	0.0069930070	0.5	0.8586	0.8516	3
x + x_hat + skips	x_hat + skips	0.0015540016	0.75	0.8586	0.8570	3
x + x_hat + skips	x + skips	0.0023310023	0.5	0.8586	0.8563	3
x + x_hat + skips	skips	0.0182595183	0.25	0.8586	0.8403	3
x + x_hat + skips	z only	0.0077700078	0.75	0.8586	0.8508	3
x + x_hat + skips	z + x	0.0097125097	0.25	0.8586	0.8489	3
x + x_hat + skips	z + x_hat	0.0069930070	0.25	0.8586	0.8516	3
x + x_hat + skips	z + skips	0.0054380054	0.5	0.8586	0.8531	3
x + x_hat	x_hat + skips	-0.0054380054	0.75	0.8516	0.8570	3
x + x_hat	x + skips	-0.0046610047	0.5	0.8516	0.8563	3
x + x_hat	skips	0.0112665113	0.25	0.8516	0.8403	3
x + x_hat	z only	0.0007770008	1.0	0.8516	0.8508	3
x + x_hat	z + x	0.0027195027	0.5	0.8516	0.8489	3
x + x_hat	z + x_hat	0.0000000000	1.0	0.8516	0.8516	3
x + x_hat	z + skips	-0.0015540016	0.75	0.8516	0.8531	3
x_hat + skips	x + skips	0.0007770008	1.0	0.8570	0.8563	3
x_hat + skips	skips	0.0167055167	0.5	0.8570	0.8403	3
x_hat + skips	z only	0.0062160062	0.75	0.8570	0.8508	3
x_hat + skips	z + x	0.0081585082	0.5	0.8570	0.8489	3
x_hat + skips	z + x_hat	0.0054380054	0.25	0.8570	0.8516	3
x_hat + skips	z + skips	0.0038850039	0.5	0.8570	0.8531	3
x + skips	skips	0.0159285159	0.5	0.8563	0.8403	3
x + skips	z only	0.0054380054	0.75	0.8563	0.8508	3
x + skips	z + x	0.0073815074	0.5	0.8563	0.8489	3
x + skips	z + x_hat	0.0046610047	0.25	0.8563	0.8516	3
x + skips	z + skips	0.0031070031	0.75	0.8563	0.8531	3
skips	z only	-0.0104895105	0.25	0.8403	0.8508	3
skips	z + x	-0.0085470085	0.5	0.8403	0.8489	3
skips	z + x_hat	-0.0112665113	0.5	0.8403	0.8516	3
skips	z + skips	-0.0128205128	0.5	0.8403	0.8531	3
z only	z + x	0.0019425019	0.75	0.8508	0.8489	3
z only	z + x_hat	-0.0007770008	1.0	0.8508	0.8516	3
z only	z + skips	-0.0023310023	1.0	0.8508	0.8531	3
z + x	z + x_hat	-0.0027195027	1.0	0.8489	0.8516	3
z + x	z + skips	-0.0042735043	0.75	0.8489	0.8531	3
z + x_hat	z + skips	-0.0015540016	1.0	0.8516	0.8531	3

Table 52: Pairwise Wilcoxon test results for decoder input ablations on seen subjects in the SSVEP task

config_1	config_2	mean_diff	p_value	mean_1	mean_2	n_seeds
x + x_hat + skips	x + x_hat	-0.0128205128	0.25	0.8312	0.8440	3
x + x_hat + skips	x_hat + skips	-0.0042735043	0.75	0.8312	0.8355	3
x + x_hat + skips	x + skips	0.0138888889	0.25	0.8312	0.8173	3
x + x_hat + skips	skips	0.0053418803	1.0	0.8312	0.8259	3
x + x_hat + skips	z only	-0.0160256410	0.5	0.8312	0.8472	3
x + x_hat + skips	z + x	0.0106837607	0.25	0.8312	0.8205	3
x + x_hat + skips	z + x_hat	0.0053418803	1.0	0.8312	0.8259	3
x + x_hat + skips	z + skips	-0.0042735043	1.0	0.8312	0.8355	3
x + x_hat	x_hat + skips	0.0085470085	0.75	0.8440	0.8355	3
x + x_hat	x + skips	0.0267094017	0.25	0.8440	0.8173	3
x + x_hat	skips	0.0181623932	0.5	0.8440	0.8259	3
x + x_hat	z only	-0.0032051282	0.75	0.8440	0.8472	3
x + x_hat	z + x	0.0235042735	0.25	0.8440	0.8205	3
x + x_hat	z + x_hat	0.0181623932	0.5	0.8440	0.8259	3
x + x_hat	z + skips	0.0085470085	0.5	0.8440	0.8355	3
x_hat + skips	x + skips	0.0181623932	0.25	0.8355	0.8173	3
x_hat + skips	skips	0.0096153846	0.75	0.8355	0.8259	3
x_hat + skips	z only	-0.0117521368	0.75	0.8355	0.8472	3
x_hat + skips	z + x	0.0149572649	0.5	0.8355	0.8205	3
x_hat + skips	z + x_hat	0.0096153846	0.75	0.8355	0.8259	3
x_hat + skips	z + skips	0.0000000000	1.0	0.8355	0.8355	3
x + skips	skips	-0.0085470085	1.0	0.8173	0.8259	3
x + skips	z only	-0.0299145299	0.5	0.8173	0.8472	3
x + skips	z + x	-0.0032051282	0.75	0.8173	0.8205	3
x + skips	z + x_hat	-0.0085470085	1.0	0.8173	0.8259	3
x + skips	z + skips	-0.0181623932	0.5	0.8173	0.8355	3
skips	z only	-0.0213675214	0.25	0.8259	0.8472	3
skips	z + x	0.0053418803	1.0	0.8259	0.8205	3
skips	z + x_hat	0.0000000000	1.0	0.8259	0.8259	3
skips	z + skips	-0.0096153846	0.5	0.8259	0.8355	3
z only	z + x	0.0267094017	0.25	0.8472	0.8205	3
z only	z + x_hat	0.0213675214	0.25	0.8472	0.8259	3
z only	z + skips	0.0117521368	0.5	0.8472	0.8355	3
z + x	z + x_hat	-0.0053418803	1.0	0.8205	0.8259	3
z + x	z + skips	-0.0149572649	0.25	0.8205	0.8355	3
z + x_hat	z + skips	-0.0096153846	0.75	0.8259	0.8355	3

Table 53: Pairwise Wilcoxon test results for decoder input ablations on unseen subjects in the SSVEP task

config_1	config_2	mean_1	mean_2	p_value	statistic	n_seeds	p_value_corrected	significant
x + x_hat + skips	x + x_hat	0.8586	0.8516	0.5	0.00699	3	1	FALSE
x + x_hat + skips	x_hat + skips	0.8586	0.8570	0.8	0.00155	3	1	FALSE
x + x_hat + skips	x + skips	0.8586	0.8563	0.6	0.00233	3	1	FALSE
x + x_hat + skips	skips	0.8586	0.8403	0.2	0.01826	3	1	FALSE
x + x_hat + skips	z only	0.8586	0.8508	0.6	0.00777	3	1	FALSE
x + x_hat + skips	z + x	0.8586	0.8489	0.2	0.00971	3	1	FALSE
x + x_hat + skips	z + x_hat	0.8586	0.8516	0.1	0.00699	3	1	FALSE
x + x_hat + skips	z + skips	0.8586	0.8531	0.4	0.00544	3	1	FALSE
x + x_hat	x_hat + skips	0.8516	0.8570	0.5	-0.00544	3	1	FALSE
x + x_hat	x + skips	0.8516	0.8563	0.5	-0.00466	3	1	FALSE
x + x_hat	skips	0.8516	0.8403	0.4	0.01127	3	1	FALSE
x + x_hat	z only	0.8516	0.8508	1.0	0.00078	3	1	FALSE
x + x_hat	z + x	0.8516	0.8489	0.7	0.00272	3	1	FALSE
x + x_hat	z + x_hat	0.8516	0.8516	1.0	0.00000	3	1	FALSE
x + x_hat	z + skips	0.8516	0.8531	0.9	-0.00155	3	1	FALSE
x_hat + skips	x + skips	0.8570	0.8563	0.9	0.00078	3	1	FALSE
x_hat + skips	skips	0.8570	0.8403	0.3	0.01671	3	1	FALSE
x_hat + skips	z only	0.8570	0.8508	0.7	0.00622	3	1	FALSE
x_hat + skips	z + x	0.8570	0.8489	0.3	0.00816	3	1	FALSE
x_hat + skips	z + x_hat	0.8570	0.8516	0.1	0.00544	3	1	FALSE
x_hat + skips	z + skips	0.8570	0.8531	0.5	0.00389	3	1	FALSE
x + skips	skips	0.8563	0.8403	0.3	0.01593	3	1	FALSE
x + skips	z only	0.8563	0.8508	0.7	0.00544	3	1	FALSE
x + skips	z + x	0.8563	0.8489	0.3	0.00738	3	1	FALSE
x + skips	z + x_hat	0.8563	0.8516	0.3	0.00466	3	1	FALSE
x + skips	z + skips	0.8563	0.8531	0.6	0.00311	3	1	FALSE
skips	z only	0.8403	0.8508	0.5	-0.01049	3	1	FALSE
skips	z + x	0.8403	0.8489	0.5	-0.00855	3	1	FALSE
skips	z + x_hat	0.8403	0.8516	0.4	-0.01127	3	1	FALSE
skips	z + skips	0.8403	0.8531	0.3	-0.01282	3	1	FALSE
z only	z + x	0.8508	0.8489	0.8	0.00194	3	1	FALSE
z only	z + x_hat	0.8508	0.8516	1.0	-0.00078	3	1	FALSE
z only	z + skips	0.8508	0.8531	0.9	-0.00233	3	1	FALSE
z + x	z + x_hat	0.8489	0.8516	0.8	-0.00272	3	1	FALSE
z + x	z + skips	0.8489	0.8531	0.5	-0.00427	3	1	FALSE
z + x_hat	z + skips	0.8516	0.8531	0.9	-0.00155	3	1	FALSE

Table 54: Pairwise permutation tests of decoder input ablations on seen subjects in the SSVEP task

config_1	config_2	mean_1	mean_2	p_value	statistic	n_seeds	p_value_corrected	significant
x + x_hat + skips	x + x_hat	0.8312	0.8440	0.6	-0.0128	3	1	FALSE
x + x_hat + skips	x_hat + skips	0.8312	0.8355	0.9	-0.0043	3	1	FALSE
x + x_hat + skips	x + skips	0.8312	0.8173	0.6	0.0139	3	1	FALSE
x + x_hat + skips	skips	0.8312	0.8259	0.9	0.0053	3	1	FALSE
x + x_hat + skips	z only	0.8312	0.8472	0.6	-0.0160	3	1	FALSE
x + x_hat + skips	z + x	0.8312	0.8205	0.5	0.0107	3	1	FALSE
x + x_hat + skips	z + x_hat	0.8312	0.8259	0.9	0.0053	3	1	FALSE
x + x_hat + skips	z + skips	0.8312	0.8355	0.9	-0.0043	3	1	FALSE
x + x_hat	x_hat + skips	0.8440	0.8355	0.8	0.0085	3	1	FALSE
x + x_hat	x + skips	0.8440	0.8173	0.5	0.0267	3	1	FALSE
x + x_hat	skips	0.8440	0.8259	0.6	0.0182	3	1	FALSE
x + x_hat	z only	0.8440	0.8472	0.8	-0.0032	3	1	FALSE
x + x_hat	z + x	0.8440	0.8205	0.5	0.0235	3	1	FALSE
x + x_hat	z + x_hat	0.8440	0.8259	0.7	0.0182	3	1	FALSE
x + x_hat	z + skips	0.8440	0.8355	0.6	0.0085	3	1	FALSE
x_hat + skips	x + skips	0.8355	0.8173	0.6	0.0182	3	1	FALSE
x_hat + skips	skips	0.8355	0.8259	0.8	0.0096	3	1	FALSE
x_hat + skips	z only	0.8355	0.8472	0.9	-0.0118	3	1	FALSE
x_hat + skips	z + x	0.8355	0.8205	0.6	0.0150	3	1	FALSE
x_hat + skips	z + x_hat	0.8355	0.8259	0.7	0.0096	3	1	FALSE
x_hat + skips	z + skips	0.8355	0.8355	1.0	0.0000	3	1	FALSE
x + skips	skips	0.8173	0.8259	0.9	-0.0085	3	1	FALSE
x + skips	z only	0.8173	0.8472	0.6	-0.0299	3	1	FALSE
x + skips	z + x	0.8173	0.8205	0.9	-0.0032	3	1	FALSE
x + skips	z + x_hat	0.8173	0.8259	0.8	-0.0085	3	1	FALSE
x + skips	z + skips	0.8173	0.8355	0.7	-0.0182	3	1	FALSE
skips	z only	0.8259	0.8472	0.5	-0.0214	3	1	FALSE
skips	z + x	0.8259	0.8205	1.0	0.0053	3	1	FALSE
skips	z + x_hat	0.8259	0.8259	1.0	0.0000	3	1	FALSE
skips	z + skips	0.8259	0.8355	0.6	-0.0096	3	1	FALSE
z only	z + x	0.8472	0.8205	0.5	0.0267	3	1	FALSE
z only	z + x_hat	0.8472	0.8259	0.6	0.0214	3	1	FALSE
z only	z + skips	0.8472	0.8355	0.6	0.0118	3	1	FALSE
z + x	z + x_hat	0.8205	0.8259	0.9	-0.0053	3	1	FALSE
z + x	z + skips	0.8205	0.8355	0.5	-0.0150	3	1	FALSE
z + x_hat	z + skips	0.8259	0.8355	0.8	-0.0096	3	1	FALSE

Table 55: Pairwise permutation tests of decoder input ablations on unseen subjects in the SSVEP task