Imagined Speech in Spanish: EEG Dataset Acquisition Protocol and Baseline Classification Results

Luis-Raul Sigala-Gonzalez, Graciela Ramirez-Alonso, Juan A. Ramirez-Quintana, Fernando Martinez-Reyes, and David R. Lopez-Flores

***Abstract*—This work presents a new Spanish-language electroencephalography (EEG) dataset for imagined speech, designed to support research in brain–computer interface (BCI) applications for assistive communication. A structured experimental protocol was developed to guide the acquisition process, incorporating auditory comprehension, imagined speech, and articulated speech production stages to enhance cognitive engagement and enable signal validation. The dataset includes 16 participants (9 male and 7 female), each performing 14 linguistic prompts consisting of nine words and five vowels. EEG signals were recorded using an open-source, low-cost acquisition system (OpenBCI Cyton + Daisy) with 16 channels configured according to the international 10–20 system. The collected signals were preprocessed, segmented, and evaluated through a deep learning classification framework adapted from recent imagined speech decoding approaches. Five classification experiments were conducted to assess the discriminability of the imagined speech signals. The results showed accuracies above the chance level across all experiments, achieving 30.79% ± 4.76 for vowel classification, 20.81% ± 3.11 for word classification, and up to 74.61% ± 7.11 for binary word–vowel discrimination. Comparisons with public datasets demonstrated that the proposed dataset achieves competitive or superior performance despite using low-cost hardware. The code used in this work is available at https://github.com/GracielaRamirezA/Imagined-Speech-in-Spanish.git.**

Link to graphical and video abstracts, and to code:
https://latamt.ieeer9.org/index.php/transactions/article/view/10609

***Index Terms*—Imagined speech, EEG dataset, BCI, low-cost hardware, neural signal classification.**

I. Introduction

SPEECH is the primary form of human communication used to express thoughts, emotions, and intentions through articulated sounds and words [1], [2]. The production of speech is a complex neuromuscular process that requires coordinated movements of the tongue, lips, jaw, and vocal folds. This process is primarily controlled by Broca's and Wernicke's areas in the cerebral cortex [3]. Together, these regions enable the motor execution of speech and the comprehension of spoken language.

Language impairments represent a significant challenge in clinical neuroscience and communication research [4]. Aphasia, in particular, is a language disorder that affects approximately one-third of stroke survivors, as damage to specific brain regions can result in impairments across multiple linguistic domains, including phonology, morphology, semantics, syntax, and pragmatics [5]. Individuals with aphasia retain their cognitive ability to think, but lose the capacity to express those thoughts verbally [6]–[8]. Beyond communication limitations, affected individuals frequently experience emotional distress, depression, social isolation, and a reduced quality of life [9].

Assistive communication technologies provide alternative methods for individuals with speech and language disorders to express their thoughts and intentions. In this regard, BCIs have emerged as a promising option, as they convert neural activity into control commands for external devices, enabling communication without requiring muscular movement [10]. BCIs can rely on either invasive or non-invasive electrophysiological signals; however, EEG is the most commonly used modality because it offers a practical balance between accessibility and performance, being affordable, portable, and suitable for both clinical and non-clinical environments [11].

Different paradigms are used to generate EEG signals in BCIs, including P300 [12], motor imagery (MI) [13], and speech imagery (SI) [14]. The P300 paradigm relies on visual attention to flashing or highlighted symbols, a requirement that may limit its applicability for individuals with visual or cognitive impairments. MI-based BCIs require users to imagine motor movements, such as moving the left or right hand, the tongue, or the foot. However, these systems typically offer a limited set of commands, as the number of reliably distinguishable motor tasks is generally restricted to four. This limitation arises from EEG modulation patterns associated with event-related synchronization and desynchronization in sensorimotor rhythms [15], [16].

In contrast, the speech imagery paradigm involves imagining the articulation of phonemes, syllables, vowels, or words without producing any audible or physical speech. SI-based

The associate editor coordinating the review of this manuscript and approving it for publication was Mariel Alfaro-Ponce (*Corresponding author: Graciela Ramirez-Alonso*).

This work was supported in part by the PRODEP Program through the *Apoyo a la Incorporación de Nuevos Profesores de Tiempo Completo (NPTC)*, awarded to Graciela Ramírez-Alonso. Luis-Raul Sigala-Gonzalez acknowledges financial support from SECIHTI through graduate scholarship No. 4002072.

L. R. Sigala-Gonzalez, Graciela Ramirez-Alonso, and F. Martinez-Reyes are with the Facultad de Ingeniería, Universidad Autónoma de Chihuahua, Circuito Universitario Campus II, Chihuahua, 31125, Mexico (e-mails: lrsigala@uach.mx, galonso@uach.mx, and fmartine@uach.mx).

J. A. Ramirez-Quintana and D. R. Lopez-Flores are with the Tecnológico Nacional de México/IT Chihuahua, Chihuahua, Mexico (e-mails: juan.rq@chihuahua.tecnm.mx and david.lf@chihuahua.tecnm.mx).

BCIs have shown promise for restoring communication in individuals with aphasia by translating internally generated speech representations into external outputs [17].

Notably, public imagined-speech EEG datasets have demonstrated the feasibility of decoding multiple imagined linguistic units, including words, vowels, and phonological categories, thus offering richer command spaces than traditional motor-imagery-based systems [14].

The protocol used for EEG signal acquisition in imagined speech datasets varies across studies, particularly in terms of stimulus type, presentation modality, and the inclusion of articulated speech. In general, participants are instructed to imagine the articulation of words, syllables, or vowels without producing audible speech, focusing on the internal simulation of articulatory gestures involved in speech production.

Several representative datasets have explored this paradigm using different experimental configurations. Early work, such as the DaSalla dataset [18], focused on vowel imagery guided by visual cues, while subsequent studies expanded the vocabulary to include short and long words as well as vowels [19]. Other protocols incorporated auditory stimulation prior to imagined articulation, either through syllables [20] or full words following an auditory comprehension stage [21].

More elaborate acquisition schemes have combined imagined and articulated speech to support signal validation. Notable examples include the KaraOne dataset [22], which paired auditory and visual word presentation and required subjects to vocalize each stimulus after imagination, and the Dutch DAIS dataset [23], which adopted a similar strategy to distinguish EEG patterns associated with internal articulation from those related to articulated speech.

Spanish imagined speech datasets remain comparatively limited. Existing corpora include directional words acquired under visual stimulation, with sequential articulated and imagined stages [24], as well as datasets that combine Spanish vowels with directional commands imagined from visual prompts [25]. While these datasets have demonstrated the feasibility of decoding imagined speech in Spanish, they are typically constrained in vocabulary size or experimental scope.

Despite their relevance, most of the aforementioned datasets were acquired using high-end, clinical-grade EEG systems, such as BioSemi ActiveTwo [18], [24], BrainProducts ActiCHamp [19], Neuroscan and ANT-Neuro platforms [20]–[22], or the TMSi SAGA system [23]. Although these systems provide high-quality electrophysiological recordings, their cost and infrastructure requirements limit accessibility and reproducibility.

In contrast, the present work introduces a new imagined-speech EEG dataset acquired using the OpenBCI [1] Cyton + Daisy boards and the Ultracortex Mark IV headset, offering a substantially more accessible acquisition setup. The OpenBCI platform complies with internationally recognized standards, including CE (*Conformité Européenne*), FCC (Federal Communications Commission), and RoHS (Restriction of Hazardous Substances) certifications, supporting its suitability and reliability for EEG and BCI experimental research [2]. The central premise is that, when combined with a structured protocol, appropriate preprocessing, and a robust classification baseline, low-cost EEG systems can still yield discriminative signals suitable for imagined-speech decoding. This approach aims to broaden participation in BCI research and promote reproducible and inclusive experimental practices.

Table I summarizes the main characteristics of representative imagined-speech EEG datasets and situates the proposed dataset within the current research landscape. Based on this comparative analysis, the main contributions of the present work are as follows:

- Introduction of a publicly available Spanish imagined-speech EEG dataset acquired using low-cost OpenBCI hardware, while maintaining a structured protocol comparable to clinical-grade datasets.
- Development of a multimodal acquisition protocol combining auditory comprehension, imagined speech, and articulated speech stages for cognitive validation and comparative analysis.
- Evidence that low-cost EEG systems can preserve discriminative neural patterns for imagined-speech decoding when combined with appropriate preprocessing and acquisition strategies.
- Publication of a corpus comprising 16 participants and 14 linguistic prompts (9 words and 5 vowels), representing one of the largest Spanish imagined-speech EEG datasets reported to date.
- Adaptation of a transformer-based neural architecture as a baseline framework for imagined-speech classification using OpenBCI recordings.
- Execution of five classification experiments, including multiclass and binary tasks, providing a detailed evaluation of the separability of imagined-speech EEG patterns.
- Promotion of an accessible and reproducible BCI research framework for institutions without access to high-end EEG equipment.

The rest of this paper is organized as follows. Section II describes the dataset acquisition protocol and preprocessing. Section III reports the baseline classification results. Section IV discusses the findings and comparisons with public datasets. Finally, Section V concludes the paper.

II. Methods

For this research, the dataset generation process was structured into five stages: (*A*) design of the experimental protocol for EEG acquisition, (*B*) configuration of the data acquisition setup, (*C*) participant recruitment and selection, (*D*) segmentation and preprocessing of the recorded signals, and (*E*) validation of the resulting dataset using classification models.

A. Experimental Design

1) Word Selection: Based on the datasets reported in [24], [25], and [26], nine Spanish words (*aceptar, cancelar, arriba, abajo, derecha, izquierda, hola, ayuda,* and *gracias*) and the

[1] http://www.openbci.com

[2] https://docs.openbci.com/FAQ/Liability/

TABLE I

SUMMARY OF EXPERIMENTAL PROTOCOLS IN PUBLIC IMAGINED SPEECH EEG DATASETS. *N* DENOTES THE NUMBER OF PARTICIPANTS INCLUDED IN EACH DATASET

Dataset	Language	Stimuli Type	Task Instructions	Stimulus Mode	Articulated	*N*
DaSalla [18]	English	2 vowels (/a/, /u/)	Imagine articulation after viewing mouth-shape cue.	Visual	No	3
Arizona [19]	English	3 short/2 long words + 3 vowels	Internal imagined speech of on-screen items.	Visual	No	15
Deng et al. [20]	English	2 syllables (/ba/, /ku/)	Listen, then perform imagined speech following the specified rhythms.	Auditory	No	7
Suppes et al. [21]	English	7 words	Auditory comprehension followed by imagined speech.	Auditory	No	7
KaraOne [22]	English	7 phonemes + 4 short words	Perform imagined speech, then produce articulated speech with minimal motion.	Audio+Visual	Yes	12
DAIS [23]	Dutch	10 words	Perform imagined speech, then produce articulated speech for comparison.	Audio+Visual	Yes	20
TOL [24]	Spanish	4 directional words	Produce articulated speech first, then perform imagined speech.	Visual	Yes	10
OA [25]	Spanish	5 vowels + 6 directional words	Perform imagined speech of the visually presented stimulus.	Visual	No	15
Proposed	**Spanish**	**9 words + 5 vowels**	**Auditory comprehension $\rightarrow$ imagined speech $\rightarrow$ articulated speech.**	**Audio+Visual**	**Yes**	**16**

five Spanish vowels (/a/, /e/, /i/, /o/, /u/) were selected, defining a set of 14 experimental commands.

2) Experiment Description: The experiment shown in Figure 1 was designed for EEG acquisition, based on the protocols summarized in Table I. Each prompt was repeated 12 times per participant, and the timing of the task blocks was adjusted to minimize fatigue and maintain participant comfort throughout the session. The stages of the experimental sequence are described as follows:

- **Rest (3 s):** The participant clears their mind and prepares for the task.
- **Auditory and visual stimulus (3 s):** The participant hears the pronunciation of a word through headphones while the same word is displayed on the screen.
- **Imagined speech (2 s):** The stimuli are removed, and the participant is instructed to silently imagine articulating the word once.
- **Visual stimulus (2 s):** The same word is presented again, but without audio.
- **Imagined speech (2 s):** The participant again imagines articulating the word.
- **Visual stimulus with speech cue (2 s):** The word is displayed along with an indicator signaling that in the next stage, the participant will produce articulated speech.
- **Articulated speech (2 s):** The cues are removed, and the participant produces articulated speech once.

This sequence is repeated for each word. Each trial lasts 16 s; therefore, presenting the 14 prompts once required 224 s (3.73 min). Since each trial contained two imagined-speech stages, two imagined-speech EEG segments were obtained per prompt presentation. Each participant completed three runs of approximately 15 min within a single session. Within each run, the complete set of 14 prompts was repeated four times, resulting in 12 repetitions per prompt across the three runs and a total of 24 imagined-speech EEG segments per prompt (336 segments per participant).

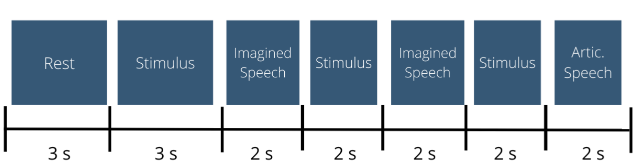


Fig. 1. Diagram of the proposed speech acquisition protocol.

3) EEG Acquisition System: The dataset was acquired using the OpenBCI Cyton + Daisy biosensing boards equipped with dry electrodes and the Ultracortex Mark IV headset. The OpenBCI Cyton + Daisy biosensing board is an open-source, integrated acquisition system operating at a sampling frequency of 125 Hertz (Hz) when used via Bluetooth. The system provides up to 16 configurable EEG channels, allowing electrode placement to be adjusted according to the requirements of the experimental protocol. The headset was modified in Shapr3D to accommodate additional electrodes at CP3, C5, and FT8, following the international 10–20 system. This configuration aligns with the recommendations in [22], where these sites showed stronger correlation with neural activity associated with imagined speech production. The final set of electrodes included FP1, C3, C5, T7, CP1, CP3, CP5, P3, FP2, FC6, FT8, C4, F8, T8, P7, and P8.

B. EEG Acquisition Setup

1) Signal Acquisition Software: A software application was developed in Python 3.11 [27] using the PyQt5 (v5.15), [28] library to support two main tasks:

1) Present the auditory and visual stimuli to the participant and indicate when to perform the imagined speech or speech response.

2) Monitor the participant's EEG activity in real time during acquisition, enabling the detection of artifacts or anomalies throughout the session.

C. Participant Recruitment and Selection

1) Participants: Following the protocols described in [22], [25], [19], and [24], a sample of 16 adult participants was recruited, all of whom were students at the Universidad Autónoma de Chihuahua.

2) Participant Selection and Invitation: Participants were initially grouped according to gender, and 10 individuals from each group were randomly selected through a lottery procedure. However, only 16 participants completed the EEG acquisition sessions (9 male and 7 female), as some invited volunteers did not attend the scheduled recording sessions. No exclusion criteria were applied after recruitment. Each participant received an invitation containing the experiment guidelines and was scheduled for a recording session. Upon arrival, the participant was briefed on the study procedures and then signed the informed consent form, which was also signed by the researcher. The study protocol was reviewed and approved by the Bioethics Committee of the Universidad Autónoma de Chihuahua (Approval No. DIP/4/419/25). The experiment was conducted in accordance with the Declaration of Helsinki.

D. Signal Preprocessing and Segmentation

The acquired signals were stored in `.npz` files as an 18-row matrix with a number of columns corresponding to the total recording duration. The first 16 rows represent the EEG channels, while rows 17 and 18 store timestamp markers corresponding to the displayed word and the experimental stage, respectively.

1) Re-referencing and Signal Filtering: The EEG signals were re-referenced by subtracting the average signal across all electrodes from each channel. An 8th-order Butterworth band-pass filter with cutoff frequencies of 8 Hz and 62 Hz was then applied. Additionally, a 60 Hz notch filter (Butterworth, quality factor = 30) was applied to all channels to attenuate power-line interference.

2) Signal Segmentation: The EEG recordings were segmented according to the experimental stage markers and organized by the corresponding word prompt. Segments for each participant were stored in individual `.npz` files. The resulting segmentation distribution is shown in Table II.

TABLE II
SEGMENTATION OF TRIALS PER PROMPT

Segment Type	Segments per Prompt
Imagined speech	24
Articulated speech	12
Relaxation	12
Auditory + visual stimulus	12
Visual stimulus	12
Speech cue	12

E. Dataset Validation

To validate the dataset, two classification tasks were defined to assess whether the acquired EEG signals contained discriminative information suitable for imagined speech decoding. During the preliminary stage of this work, different EEG classification approaches reported in the literature, including shallow convolutional architectures and one-dimensional convolution (Conv1D)–recurrent neural network (RNN)-based models, were explored as potential baseline frameworks [29], [30]. Among the evaluated configurations, the architecture adapted from [31], which combines Conv1D layers with lightweight Transformer-based strategies, achieved the most consistent performance on the proposed dataset and was therefore selected for the validation experiments.

After selecting the architecture, the original framework, including the Randomized Leaky Rectified Linear Unit (RReLU) activation function, a variant of the Rectified Linear Unit (ReLU), was preserved and adapted to the characteristics of the EEG signals acquired with the OpenBCI system. Specifically, the input structure, sampling frequency settings, and output layer dimensions were adjusted based on the acquisition setup and the number of classes for each classification task.

Fig. 2 presents the resulting architecture. The model comprises an initial batch normalization layer, followed by two parallel Conv1D branches that extract spatial and temporal EEG patterns. Each branch feeds a transformer encoder—a Spatial Transformer Encoder in the first branch and a Temporal Transformer Encoder in the second—with an upsampling operation applied to the temporal pathway to preserve dimensional consistency. The outputs of both encoders are then summed and passed to a second transformer encoder, which captures higher-level long-range dependencies.

The classification stage consists of a batch normalization layer, a flattening operation, and a dense layer, followed by dropout for regularization. The final fully connected layer produces the output, with the number of neurons corresponding to the classes defined in each classification task. For all experiments, the model was trained using the Cross-Entropy Loss function.

1) Imagined vs. Articulated Speech: The first classification task aims to discriminate between imagined-speech and articulated-speech EEG segments in order to assess the separability of their underlying neural patterns. This experiment serves as an initial validation step, verifying that the acquisition protocol produces distinguishable EEG activity associated with internal speech imagery and articulated speech. The experimental setup follows the validation strategy reported in [23].

2) Imagined Speech Classification Experiments: To further evaluate the discriminative content of the proposed dataset, five imagined-speech classification experiments were defined using different class configurations. These experiments assess multiclass discrimination, the separation between words and vowels, and the pairwise discrimination of selected linguistic units. All experiments were conducted using the same classification architecture, with the output layer adjusted according to the number of classes in each case. Table III summarizes the label assignments for the defined experimental settings.

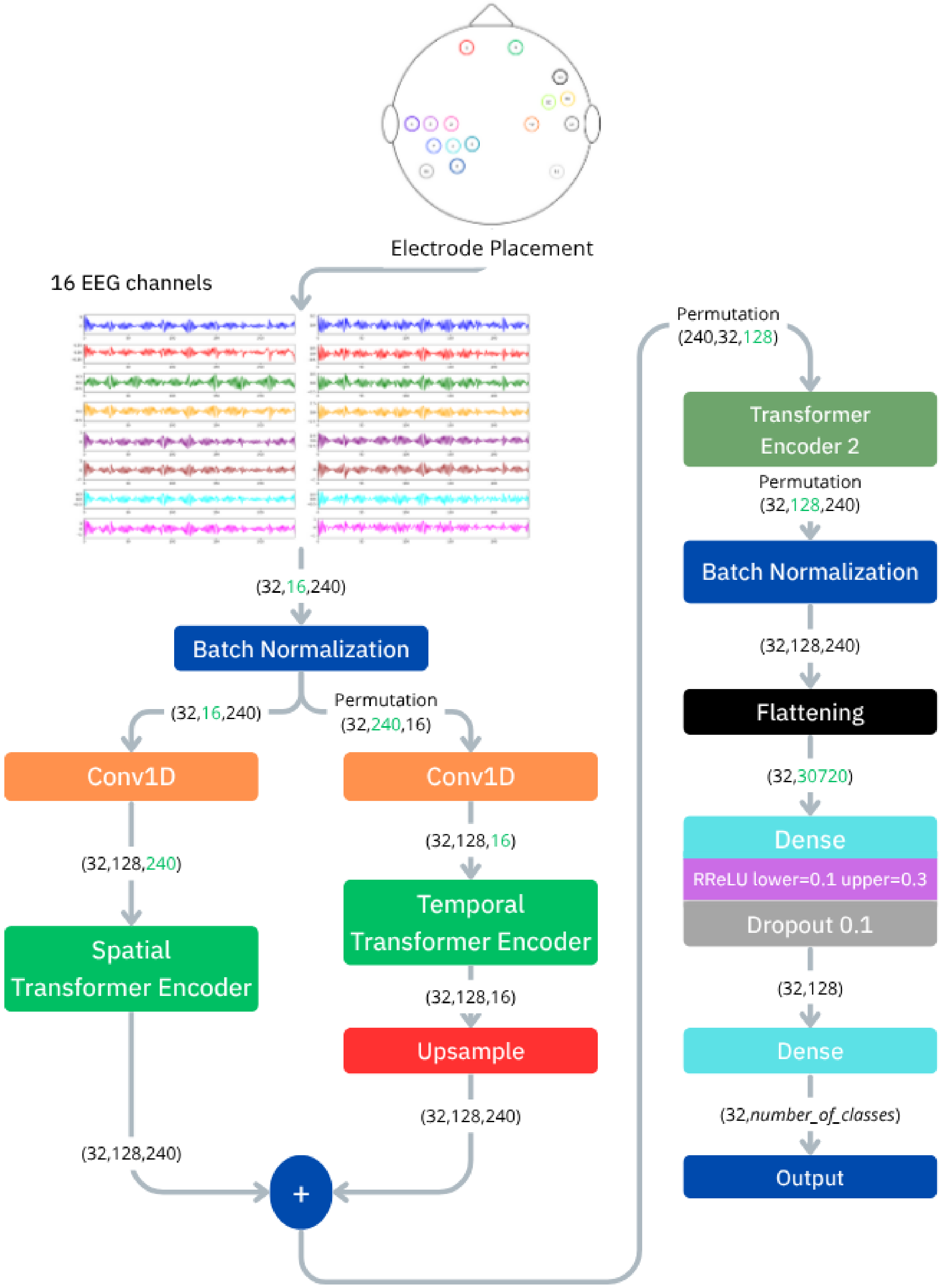


Fig. 2. Transformer-based neural architecture used for imagined-speech classification

III. Results

A. Participant Sample

EEG recordings were obtained from 16 participants (9 male and 7 female), with a mean age of 22.21 $\pm$ 3.92 years. All participants completed a single recording session and successfully followed the experimental protocol.

B. Experimental Outcomes

1) Generated Imagined Speech Segments: For 13 of the 16 participants, the number of recorded segments matched the expected distribution defined in Table II, consisting of 24 imagined-speech segments per word and 12 segments for each of the remaining stages. Minor deviations were observed

TABLE III
LABEL ASSIGNMENT FOR EACH CLASSIFICATION EXPERIMENT

Class	E1	E2	E3	E4	E5
aceptar	0	0	-	-	-
cancelar	1	1	-	-	-
arriba	2	2	-	0	-
abajo	3	3	-	0	-
derecha	4	4	-	0	-
izquierda	5	5	-	0	0
hola	6	6	-	0	-
ayuda	7	7	-	-	-
gracias	8	8	-	-	-
/a/	9	-	0	1	-
/e/	10	-	1	1	-
/i/	11	-	2	1	1
/o/	12	-	3	1	-
/u/	13	-	4	1	-

E1: 14-class experiment (all 9 words + all 5 vowels).
E2: Words-only multiclass (9 words).
E3: Vowels-only multiclass (5 vowels).
E4: 5 words vs vowels (words=0, vowels=1).
E5: 1 word vs 1 vowel (*izquierda* vs /i/).

in three cases. Participant 5 produced 30 imagined-speech segments per word and 15 segments for the remaining stages, whereas Participant 6 completed 16 and 8 segments, respectively, due to reported fatigue during the session. Participant 11 generated two additional imagined-speech segments and one additional segment for the remaining stages, resulting in a total of 384 imagined-speech segments for that participant. Since the classification results were computed independently for each participant, these cases resulted in different numbers of training samples for the corresponding subject-specific models. However, balanced class distributions were maintained within each participant across all classification experiments.

2) Adverse Events and Experimental Errors: During data acquisition, occasional hardware-related interruptions required restarting the EEG system. On average, 2.68 ± 1.25 interruptions were observed per participant. These events did not affect the stored dataset, as corrupted trials were discarded and the acquisition was resumed without altering the experimental protocol. Non-critical adverse events were also recorded, mainly temporary electrode disconnections, which appear in the data as channels with zero-valued samples. Table IV summarizes the affected channels and the number of participants in which these events occurred. No channels were excluded during preprocessing or classification, and all recordings remained suitable for subsequent analysis.

C. Signal Classification

1) Classification of Imagined vs. Articulated Speech Stages: EEG segments corresponding to imagined and articulated speech were classified to evaluate the separability of their underlying neural patterns. To assess result stability and repeatability, the experiment was independently repeated 10 times. This procedure yielded an average classification accuracy of $78.95\% \pm 1.89$. The corresponding confusion matrix is shown in Fig. 3.

2) Imagined Speech Classification: For each experimental configuration, the classification model was trained and validated independently 10 times per participant. The mean classification accuracy and standard deviation (SD) were computed, and all results are reported as mean ± SD. A quantitative summary of all results is reported in Table V.

TABLE IV
NUMBER OF PARTICIPANTS IN WHICH EEG CHANNELS WERE DISCONNECTED DURING ACQUISITION

Channel	CP3	CP1	P3	CP5	FP1	F8	T8	C3	P8
Participants	9	5	3	2	2	1	1	1	1

IV. DISCUSSION

A. Comparison of the Participant Sample with Public Datasets

The participant sample in this study consisted of 56.25% male and 43.75% female, reflecting a balanced gender distribution. Among the five publicly available imagined speech datasets considered, only the dataset reported by [25] exhibits a comparable proportion (53.33% male, 46.66% female). This alignment supports fair performance comparisons across datasets, as gender-related variability is unlikely to account for differences in classification accuracy.

B. Signal Acquisition Errors in the EEG Device

Signal acquisition errors were primarily attributable to hardware limitations of the wireless EEG system. Specifically, the device relies on an internal buffer that temporarily stores EEG samples before transmitting data packets to the host computer. Although this mechanism enables wireless operation, it can lead to data corruption or buffer overflow events, resulting in invalid EEG packets when transmission errors occur [32]. When such events were detected, the acquisition was resumed by restarting the device. The custom acquisition software allowed trials to be paused and continued without restarting the entire session. During preprocessing, corrupted segments were automatically identified and excluded from further analysis.

The feasibility of using low-cost OpenBCI-based EEG hardware for BCI applications has been previously reported in [33], showing that occasional disconnections and the inherent limitations of low-cost acquisition systems do not prevent the recording of EEG signals suitable for BCI analysis when compared with clinical-grade configurations under controlled conditions. Consistent with these observations, the classification performance obtained in this work remained stable across

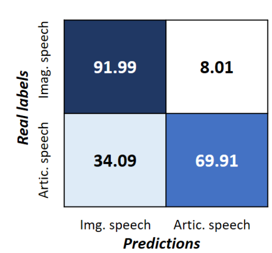


Fig. 3. Confusion matrix for imagined and articulated speech classification.

TABLE V
CLASSIFICATION ACCURACY (%) REPORTED AS MEAN ± SD ACROSS ALL PARTICIPANTS FOR THE FIVE IMAGINED-SPEECH EXPERIMENTS: E1:14-MULTICLASS (9 WORDS + 5 VOWELS); E2:WORDS-ONLY MULTICLASS (9 WORDS); E3:VOWELS-ONLY MULTICLASS (5 VOWELS); E4:WORDS VS. VOWELS (WORDS=0, VOWELS=1); E5:BINARY CLASSIFICATION BETWEEN THE WORD *Izquierda* AND THE VOWEL /I/

Subject	**E1**	**E2**	**E3**	**E4**	**E5**
1	13.37 ± 2.09	18.62 ± 3.67	29.44 ± 3.56	63.06 ± 3.12	80.67 ± 4.67
2	12.57 ± 1.00	19.23 ± 1.98	29.44 ± 3.56	67.36 ± 1.12	90.00 ± 6.15
3	11.58 ± 0.77	20.62 ± 1.97	26.94 ± 2.17	60.97 ± 3.43	74.67 ± 4.00
4	13.47 ± 0.91	17.23 ± 1.66	34.72 ± 3.98	64.44 ± 1.88	72.00 ± 4.00
5	30.87 ± 1.57	30.49 ± 1.75	39.33 ± 3.30	67.33 ± 2.00	60.56 ± 4.61
6	14.85 ± 2.23	22.73 ± 2.27	40.83 ± 2.50	64.79 ± 2.18	74.00 ± 8.00
7	12.87 ± 0.99	23.69 ± 2.40	28.33 ± 3.89	68.47 ± 2.41	68.00 ± 7.18
8	11.49 ± 0.91	18.46 ± 2.18	29.44 ± 3.97	63.19 ± 1.28	82.67 ± 3.27
9	13.66 ± 0.59	19.08 ± 2.40	27.22 ± 2.72	60.14 ± 1.97	70.00 ± 4.47
10	11.88 ± 0.89	17.23 ± 2.04	27.78 ± 3.29	60.69 ± 2.49	84.00 ± 8.00
11	13.73 ± 1.18	21.41 ± 2.25	31.03 ± 2.68	54.49 ± 3.21	72.50 ± 5.73
12	15.35 ± 1.49	21.54 ± 1.69	32.50 ± 4.13	62.36 ± 2.10	73.33 ± 4.22
13	12.28 ± 0.66	20.00 ± 3.30	32.78 ± 5.67	59.58 ± 3.37	66.00 ± 3.59
14	13.86 ± 1.47	22.92 ± 2.00	22.22 ± 4.12	64.31 ± 2.92	74.67 ± 6.53
15	16.14 ± 1.18	20.00 ± 1.38	35.00 ± 3.77	65.83 ± 2.58	79.33 ± 5.54
16	15.35 ± 1.01	19.69 ± 1.79	25.56 ± 3.47	69.44 ± 1.76	71.33 ± 6.00
Mean	**14.58 ± 4.42**	**20.81 ± 3.11**	**30.79 ± 4.76**	**63.53 ± 3.72**	**74.61 ± 7.11**

participants despite isolated acquisition errors. Although direct electrode impedance comparisons with clinical-grade EEG systems were not performed in this study, the obtained results further support the feasibility of low-cost EEG systems for imagined-speech decoding tasks.

C. Validation of the Proposed Dataset

According to the results presented in Table V, the five experiments (E1–E5) provide clear evidence of discriminative neural patterns in the proposed dataset.

E1 (14-class multiclass) achieved an average accuracy of 14.58% ± 4.42, which is more than double the theoretical chance level (7%). Although this represents the most challenging configuration, combining all nine words and five vowels, participants still produced separable patterns, a result rarely reported in imagined-speech research due to the inherent difficulty of large multiclass settings.

E2 (words-only multiclass) reached a mean accuracy of 20.81% ± 3.11, also above chance level and consistent with findings from public datasets with comparable vocabulary sizes. This outcome suggests that the imagined production of Spanish words yields identifiable EEG signatures, even when acquired using low-cost hardware.

E3 (vowels-only multiclass) yielded the highest multiclass accuracy (30.79% ± 4.76). The superior performance with vowels aligns with previous studies, which show that vowel imagery typically produces clearer cortical activation patterns than words, likely due to simpler articulatory representations.

In the binary configurations, E4 (words vs. vowels) obtained 63.53% ± 3.72, substantially exceeding the 50% chance level. This separation reflects the strong contrast between the neural processes underlying lexical items and isolated phonemic units, despite both being acquired under the same protocol.

Finally, E5 (izquierda vs. /i/)—the most constrained binary task—showed a mean accuracy of 74.61% ± 7.11, indicating robust discriminability even between two linguistically related prompts (a word beginning with the same vowel). This result reinforces the presence of consistent, class-specific EEG patterns across participants.

Together, these outcomes demonstrate that the imagined-speech EEG signals collected with the proposed acquisition setup contain sufficient discriminative structure to support both multiclass and binary classification, laying the foundation for meaningful comparisons with public datasets in the next section.

A Wilcoxon signed-rank test was conducted for all classification experiments to determine whether the observed accuracies were significantly higher than their corresponding theoretical chance levels. All comparisons yielded statistically significant differences ($p < 0.001$). These results provide strong evidence that the classifiers captured meaningful discriminative EEG patterns rather than achieving the observed performance through random chance.

Additional analyses were conducted to evaluate inter-subject variability and its possible relationship with processed EEG signal features. Metrics, including RMS amplitude, variance, signal power, and beta-band power, were analyzed across participants. The Shapiro–Wilk test indicated that the normality assumption was rejected for all analyzed variables ($p < 0.05$). Therefore, correlations were assessed using Spearman's rank correlation coefficient. No statistically significant correlations were found between the evaluated EEG signal metrics and classification performance (all $p > 0.05$). Likewise, no clear association was identified between reported channel disconnections and classification accuracy. These observations suggest that the observed inter-subject variability may be influenced by subject-dependent neurophysiological and cognitive factors, such as differences in attention, mental task engagement, or consistency in imagined speech generation, beyond the evaluated EEG signal features.

D. Dataset and Code Availability

The preprocessing scripts, segmentation procedures, and baseline classification implementation used in this work are publicly available in the project repository: https://github.com/GracielaRamirezA/Imagined-Speech-in-Spanish.git. The repository also includes instructions for dataset access and reuse.

E. Comparison of Classification Performance with Public Datasets

To contextualize the performance of the baseline classification model on the proposed dataset, its results were compared with classification accuracies reported for publicly available imagined-speech EEG datasets. This analysis aims to assess the relative discriminative capability of the proposed dataset under comparable experimental settings.

In [25], the classification accuracy reported for Spanish vowel imagery was $22.72\%\pm1.81$, whereas our baseline model achieved $30.79\%\pm4.76$ when evaluated on the vowel segments of the proposed dataset. Similarly, [25] reported an accuracy of $19.6\%\pm1.47$ for the classification of six Spanish directional words (*arriba*, *abajo*, *derecha*, *izquierda*, *adelante*, and *atrás*). To enable a fair comparison under the same class cardinality, the words *adelante* and *atrás*, which are not included in the proposed protocol, were replaced by *aceptar* and *cancelar*. Under this six-class configuration, the model achieved an accuracy of $21.55\% \pm 0.24$ on the proposed dataset. Overall, these results indicate comparable or improved performance relative to the values reported in [25] for both vowel and word classification tasks.

A similar analysis can be made with the dataset introduced in [19]. In that study, the authors reported an accuracy of $49.0\%\pm2.4$ for the classification of the imagined English vowels *a*, *i*, and *u*, considering a subset of eight participants. When the classification task was restricted to the same three vowels, our baseline model achieved an accuracy of $50.00\% \pm 7.73$ when evaluated across all 16 participants in the proposed dataset. To further align the evaluation in terms of participant count, the experiment was also performed on a subset of eight participants, yielding an accuracy of $56.63\% \pm 4.20$.

The same study in [19] also reported a binary classification task distinguishing long and short English words (e.g., *out* vs. *independent*), achieving an accuracy of $80.1\% \pm 8.0$ when evaluated on six participants. As these specific words are not included in the proposed dataset, the Spanish words *hola* (short) and *izquierda* (long) were selected to approximate the characteristics of the task. Under this binary configuration, the model achieved an accuracy of $75.87\% \pm 12.97$ across all 16 participants. When the comparison was restricted to six participants to match the experimental setting of [19], the mean accuracy increased to $90.45\% \pm 6.76$, indicating comparable or improved performance under matched conditions.

Finally, to compare the performance of the adapted classification architecture used in this study, the obtained results were contrasted with those reported in [31], where the model was evaluated on the dataset introduced in [24]. In that work, a classification accuracy of $40.8\% \pm 3.6$ was reported for the discrimination of the words *arriba*, *abajo*, *derecha*, and *izquierda*. When the number of classes in the *Words* experiment of the proposed dataset was reduced to match this four-class configuration, the baseline model achieved an accuracy of $45.75\% \pm 6.65$. To further align the evaluation in terms of participant count, the experiment was also performed using the same number of subjects as in [31], yielding an accuracy of $51.11\%\pm5.12$. Overall, these results indicate comparable or improved performance under matched experimental conditions.

Although the obtained classification results remain moderate in the multiclass configuration, the primary objective of this work is not the development of a state-of-the-art imagined-speech classifier, but rather the introduction and validation of a new Spanish imagined-speech EEG dataset acquired using low-cost hardware. In this context, the implemented classification framework mainly serves to verify that the proposed acquisition protocol and preprocessing methodology preserve discriminative neural patterns suitable for imagined-speech decoding. It should also be noted that the participant sample size, although comparable to those of publicly available imagined-speech EEG datasets, remains relatively limited for broad population-level generalization.

F. Channel-wise Ablation Analysis

This section investigates the contribution of individual EEG channels to classification performance. A channel-wise ablation study was performed across the five experimental configurations by systematically removing one channel at a time and evaluating the corresponding variation in accuracy over 10 independent runs. Channel importance was computed as the mean difference between the baseline accuracy and the accuracy obtained after removing the corresponding channel. Due to the high inter-subject variability commonly observed in EEG signals, the study was conducted using Subject 5, as this participant achieved the highest overall classification performance. Fig. 4 presents the resulting topographic importance maps.

The results revealed that the spatial contribution of EEG channels varied depending on the evaluated task. In the 14-class configuration (E1), channels FC6 and P7 showed the highest importance, suggesting involvement of frontal-central and parietal regions, whereas C5 showed limited contribution. In the words-only experiment (E2), channels C5 and T7 were among the most relevant, indicating the participation of central and temporal regions, whereas Fp2 showed low relevance. For the vowels-only task (E3), channels P8 and P7 presented

TABLE VI
COMPARISON OF AVERAGE CLASSIFICATION ACCURACY (%) WITH PUBLIC IMAGINED SPEECH EEG DATASETS. THE VARIABLE n DENOTES THE NUMBER OF PARTICIPANTS CONSIDERED IN EACH EXPERIMENT

Dataset	E3	Words (6 classes)	Vowels (3 classes)	Long vs. Short Words	Words (4 classes)
OA [25] (n = 20)	22.72 ± 1.81	19.6 ± 1.47	–	–	–
Arizona [19] (n = 8, 6)	–	–	49.00 ± 2.40	80.10 ± 8.00	–
TOL [31] (n = 10)	–	–	–	–	40.80 ± 3.60
Proposed (n = 16)	**30.79 ± 4.76**	**21.55 ± 0.24**	50.00 ± 7.73	75.87 ± 12.97	45.75 ± 6.65
Proposed (n = 8, 6)	–	–	**56.63 ± 4.20**	**90.45 ± 6.76**	–
Proposed (n = 10)	–	–	–	–	**51.11 ± 5.12**

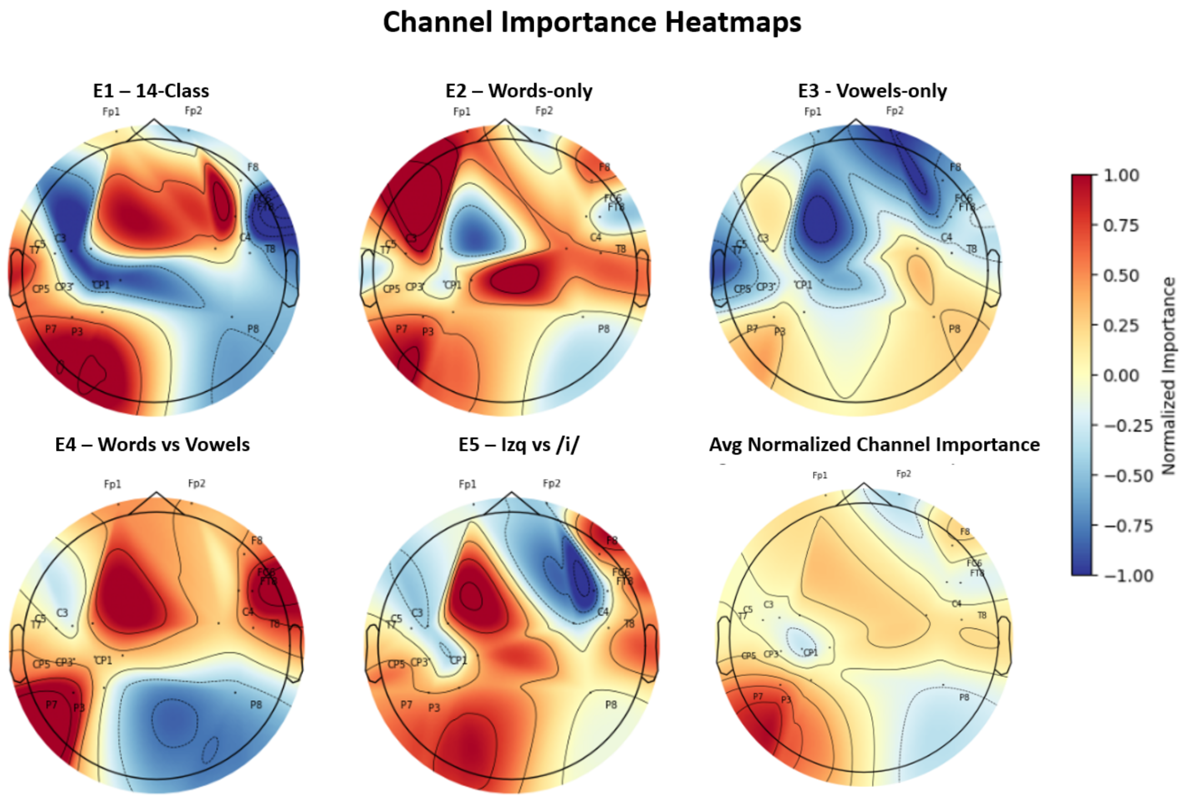


Fig. 4. EEG channel importance maps obtained from the channel-wise ablation analysis for the five experimental configurations using Subject 5.

the highest importance, emphasizing the role of parietal regions, while Fp2 exhibited negative importance values. In the words-versus-vowels configuration (E4), channels P7 and FT8 showed the strongest contribution, suggesting relevant activity in parietal and temporal regions, whereas P8 exhibited limited contribution. Finally, in the binary "izq" versus "/i/" experiment (E5), channels F8 and P7 were identified as the most discriminative, indicating the involvement of frontal and parietal regions, while FC6 exhibited negative importance values.

Overall, the identified discriminative channels were predominantly located over frontal, temporal, and parietal regions, which are spatially close to cortical areas associated with language processing, including Broca's and Wernicke's regions. According to the literature, these areas play a central role in speech planning, phonological processing, and imagined-speech generation [34]. Therefore, the observed channel importance distributions are consistent with previously reported neurophysiological findings in imagined-speech EEG studies.

V. CONCLUSION

This work presents the development of a new EEG dataset for imagined speech, supported by a structured acquisition protocol that encompasses participant selection, stimulus definition, experimental design, signal preprocessing, and classification-based validation.

The obtained classification results indicate that the proposed dataset preserves discriminative imagined-speech EEG patterns suitable for baseline decoding tasks. Furthermore, the implemented framework demonstrates the feasibility of using low-cost, open-source hardware for imagined-speech analysis under controlled experimental conditions.

By releasing this dataset to the research community, we aim to facilitate replication, benchmarking, and methodological improvements, encouraging collaborative progress in imagined-speech decoding and accessible brain–computer interface research.

As future work, we plan to investigate alternative lightweight classification architectures that improve decoding performance while maintaining low computational cost, enabling deployment on resource-constrained devices.

In summary, the proposed dataset constitutes a practical and accessible resource for advancing imagined-speech BCI research and has the potential to support the development of assistive communication technologies for individuals with speech impairments.

Acknowledgments

This work was supported by the PRODEP Program through the *Apoyo a la Incorporación de Nuevos Profesores de Tiempo Completo (NPTC)*, awarded to Graciela Ramirez-Alonso. Luis-Raul Sigala-Gonzalez acknowledges financial support from SECIHTI through graduate scholarship No. 4002072.

The authors declare the use of ChatGPT (OpenAI) for language editing and grammar improvement during manuscript preparation. All scientific content, analyses, results, and conclusions were developed and verified by the authors.

References

[1] J. L. Freeburn and J. Baker, "Functional speech and voice disorders: Approaches to diagnosis and treatment," *Neurologic Clinics*, vol. 41, no. 4, pp. 635–646, 2023, https://doi.org/10.1016/j.ncl.2023.02.005.

[2] N. M. Sharma, V. Kumar, P. K. Mahapatra, and V. Gandhi, "Comparative analysis of various feature extraction techniques for classification of speech disfluencies," *Speech Communication*, vol. 150, pp. 23–31, 2023, https://doi.org/10.1016/j.specom.2023.04.003.

[3] G. Hickok and D. Poeppel, "Dorsal and ventral streams: a framework for understanding aspects of the functional anatomy of language," *Cognition*, vol. 92, no. 1, pp. 67–99, 2004, https://doi.org/10.1016/j.cognition.2003.10.011.

[4] W. A. Awuah, A. Ahluwalia, K. Darko, V. Sanker, J. K. Tan, P. O. Tenkorang, A. Ben-Jaafar, S. Ranganathan, N. Aderinto, A. Mehta, M. H. Shah, K. Lee Boon Chun, T. Abdul-Rahman, and O. Atallah, "Bridging minds and machines: The recent advances of brain-computer interfaces in neurological and neurosurgical applications," *World Neurosurgery*, vol. 189, pp. 138–153, 2024, https://doi.org/10.1016/j.wneu.2024.05.104.

[5] S. T. Engelter, M. Gostynski, S. Papa, M. Frei, C. Born, V. Ajdacic-Gross, F. Gutzwiller, and P. A. Lyrer, "Epidemiology of aphasia attributable to first ischemic stroke," *Stroke*, vol. 37, no. 6, pp. 1379–1384, 2006, https://doi.org/10.1161/01.STR.0000221815.64093.8c.

[6] G.-J. Rutten, "Chapter 2 - broca-wernicke theories: A historical perspective," in *Aphasia*, ser. Handbook of Clinical Neurology, A. E. Hillis and J. Fridriksson, Eds. Elsevier, 2022, vol. 185, pp. 25–34, https://doi.org/10.1016/B978-0-12-823384-9.00001-3.

[7] A. B. Acharya and S. C. Dulebohn, "Broca aphasia," *StatPearls*, 5 2022, https://www.ncbi.nlm.nih.gov/books/NBK436010/.

[8] F. Lui and M. Wroten, "Wernicke aphasia," *StatPearls*, 11 2025, https://www.ncbi.nlm.nih.gov/books/NBK441951/.

[9] M. Purdy, "Aphasia, alexia, and agraphia," in *Encyclopedia of Mental Health (Second Edition)*, second edition ed., H. S. Friedman, Ed. Oxford: Academic Press, 2016, pp. 81–90, https://doi.org/10.1016/B978-0-12-397045-9.00056-2.

[10] J. S. Garcia-Salinas, A. A. Torres-Garcia, C. A. Reyes-Garcia, and L. Villaseñor-Pineda, "Intra-subject class-incremental deep learning approach for EEG-based imagined speech recognition," *Biomedical Signal Processing and Control*, vol. 81, p. 104433, 2023, https://doi.org/10.1016/j.bspc.2022.104433.

[11] M. Nouri, F. Moradi, H. Ghaemi, and A. Motie Nasrabadi, "Towards real-world BCI: CCSPNet, a compact subject-independent motor imagery framework," *Digital Signal Processing*, vol. 133, p. 103816, 2023, https://doi.org/10.1016/j.dsp.2022.103816.

[12] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and Clinical Neurophysiology*, vol. 70, no. 6, pp. 510–523, 1988, https://doi.org/10.1016/0013-4694(88)90149-6.

[13] S. Kumar, K. Mamun, and A. Sharma, "CSP-TSM: Optimizing the performance of riemannian tangent space mapping using common spatial pattern for MI-BCI," *Computers in Biology and Medicine*, vol. 91, pp. 231–242, 2017, https://doi.org/10.1016/j.compbiomed.2017.10.025.

[14] A. A. Torres-García, C. A. Reyes-García, and L. Villaseñor-Pineda, "Chapter 12 - a survey on EEG-based imagined speech classification," in *Biosignal Processing and Classification Using Computational Learning and Intelligence*, A. A. Torres-García, C. A. Reyes-García, L. Villaseñor-Pineda, and O. Mendoza-Montoya, Eds. Academic Press, 2022, pp. 251–270, https://doi.org/10.1016/B978-0-12-820125-1.00025-7.

[15] B. Blankertz, K.-R. Muller, D. Krusienski, G. Schalk, J. Wolpaw, A. Schlogl, G. Pfurtscheller, J. Millan, M. Schroder, and N. Birbaumer, "The BCI competition III: validating alternative approaches to actual BCI problems," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no. 2, pp. 153–159, 2006, https://doi.org/10.1109/TNSRE.2006.875642.

[16] M. Tangermann, K.-R. Muller, A. Aertsen, N. Birbaumer, C. Braun, C. Brunner, R. Leeb, C. Mehring, K. Miller, G. Mueller-Putz, G. Nolte, G. Pfurtscheller, H. Preissl, G. Schalk, A. Schlogl, C. Vidaurre, S. Waldert, and B. Blankertz, "Review of the BCI competition IV," *Frontiers in Neuroscience*, vol. 6, 2012, https://doi.org/10.3389/fnins.2012.00055.

[17] S. L. Metzger, K. T. Littlejohn, A. B. Silva, D. A. Moses, M. P. Seaton, R. Wang, M. E. Dougherty, J. R. Liu, P. Wu, M. A. Berger *et al.*, "A high-performance neuroprosthesis for speech decoding and avatar control," *Nature*, vol. 620, no. 7976, pp. 1037–1046, 2023, https://doi.org/10.1038/s41586-023-06443-4.

[18] C. S. DaSalla, H. Kambara, M. Sato, and Y. Koike, "Single-trial classification of vowel speech imagery using common spatial patterns," *Neural Networks*, vol. 22, no. 9, pp. 1334–1339, 2009, https://doi.org/10.1016/j.neunet.2009.05.008.

[19] C. H. Nguyen, G. K. Karavas, and P. Artemiadis, "Inferring imagined speech using EEG signals: a new approach using Riemannian manifold features," *Journal of Neural Engineering*, vol. 15, no. 1, p. 016002, 12 2017, https://doi.org/10.1088/1741-2552/AA8235.

[20] S. Deng, R. Srinivasan, T. Lappas, and M. D'Zmura, "EEG classification of imagined syllable rhythm using hilbert spectrum methods," *Journal of Neural Engineering*, vol. 7, no. 4, p. 046006, jun 2010, https://doi.org/10.1088/1741-2560/7/4/046006.

[21] P. Suppes, Z. L. Lu, and B. Han, "Brain wave recognition of words," *Proceedings of the National Academy of Sciences*, vol. 94, no. 26, pp. 14 965–14 969, 1997, https://doi.org/10.1073/PNAS.94.26.14965.

[22] S. Zhao and F. Rudzicz, "Classifying phonological categories in imagined and articulated speech," in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015, pp. 992–996, https://doi.org/10.1109/ICASSP.2015.7178118.

[23] B. Dekker, A. C. Schouten, and O. Scharenborg, "DAIS: The delft database of EEG recordings of dutch articulated and imagined speech," in *2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2023, pp. 1–5, https://doi.org/10.1109/ICASSP49357.2023.10096145.

[24] N. Nieto, V. Peterson, H. L. Rufiner, J. E. Kamienkowski, and R. Spies, "Thinking out loud, an open-access EEG-based BCI dataset for inner speech recognition," *Scientific Data*, vol. 9, no. 1, pp. 1–17, feb 2022, https://doi.org/10.1038/s41597-022-01147-2.

[25] G. A. P. Coretto, I. E. Gareis, and H. L. Rufiner, "Open access database of EEG signals recorded during imagined speech," in *12th International Symposium on Medical Information Processing and Analysis*, vol. 10160. SPIE, 2017, p. 1016002, https://doi.org/10.1117/12.2255697.

[26] J.-H. Jeong, J.-H. Cho, Y.-E. Lee, S.-H. Lee, G.-H. Shin, Y.-S. Kweon, J. d. R. Millán, K.-R. Müller, and S.-W. Lee, "2020 international brain–computer interface competition: A review," *Frontiers in Human Neuroscience*, vol. 16, 2022, https://doi.org/10.3389/fnhum.2022.898300.

[27] Python Software Foundation, "Python 3.11 documentation," https://docs.python.org/3.11/, 2024, accessed: Jul. 2026.

[28] Riverbank Computing, "PyQt5 Reference Guide," https://pypi.org/project/PyQt5/, 2024, accessed: Jul. 2026.

[29] C. M. Köllőd, A. Adolf, K. Iván, G. Márton, and I. Ulbert, "Deep comparisons of neural networks from the EEGNet family," *Electronics*, vol. 12, no. 12, 2023, https://www.mdpi.com/2079-9292/12/12/2743.

[30] A. Hernandez-Galvan, G. Ramirez-Alonso, J. Camarillo-Cisneros, G. Samano-Lira, and J. Ramirez-Quintana, "Imagined Speech Recognition in a Subject Independent Approach Using a Prototypical Network," in *XLV Mexican Conference on Biomedical Engineering*, C. J. Trujillo-Romero, R. Gonzalez-Landaeta, C. Chapa-González, G. Dorantes-Méndez, D.-L. Flores, J. J. A. F. Cuautle, M. R. Ortiz-Posadas, R. A. S. Ruiz, and E. Zuñiga-Aguilar, Eds. Cham: Springer International Publishing, 2023, pp. 37–45, https://doi.org/10.1007/978-3-031-18256-3_4.

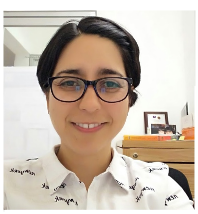
[31] I. Gallo and S. Corchs, "Thinking is like processing a sequence of spatial and temporal words," in *2024 International Joint Conference on Neural Networks (IJCNN)*, 2024, pp. 1–8, https://doi.org/10.1109/IJCNN60899.2024.10650922.

[32] M. T. Knierim, M. G. Bleichner, and P. Reali, "A systematic comparison of high-end and low-cost EEG amplifiers for concealed, around-the-ear EEG recordings," *Sensors*, vol. 23, no. 9, 2023, https://doi.org/10.3390/s23094559.

[33] V. Peterson, C. Galván, H. Hernández, and R. Spies, "A feasibility study of a complete low-cost consumer-grade brain-computer interface system," *Heliyon*, vol. 6, no. 3, 2020, https://doi.org/10.1016/j.heliyon.2020.e03425.

[34] Z. Jin, D. Li, and S. Huang, "A systematic review of EEG-based Imagined Speech decoding," *Applied Soft Computing*, vol. 183, p. 113563, 2025, https://doi.org/10.1016/j.asoc.2025.113563.

Luis R. Sigala-Gonzalez received the Bachelor's degree in Biomedical Engineering from the Universidad Autónoma de Chihuahua, Facultad de Medicina, Mexico, in 2021, and the Master's degree in Computer Engineering from the same institution, Facultad de Ingeniería, in 2025. He is currently an Adjunct Professor at the Universidad Autónoma de Chihuahua, Facultad de Medicina, where he teaches Calculus, Mechanics, and Programming Languages. His research interests include computer science, computer vision applied to the biomedical field, and the analysis and processing of biomedical signals.



Graciela Ramirez-Alonso received the M.Sc. (2004) and Ph.D. (2015) degrees in Electrical Engineering from the Tecnológico Nacional de México, IT Chihuahua. She is currently a professor at the Universidad Autónoma de Chihuahua, Facultad de Ingeniería, where she also serves as Director of the Computer Vision and Data Science Lab. She is a member of the National System of Researchers of the Secretaría de Ciencia, Humanidades, Tecnología e Innovación (SECIHTI). Her research interests include signal processing, computer vision, fuzzy logic, and machine learning algorithms.

Juan Ramirez-Quintana received the M.Sc. and Ph.D. degrees in Electronic Engineering in 2007 and 2014, respectively. He is currently a Researcher and Professor at the Tecnológico Nacional de México, IT Chihuahua, and serves as Director of the Digital Signal Processing and Artificial Intelligence Laboratory. His research interests include computer vision, signal processing, computational intelligence, and machine learning. He is a member of the National Research System of Mexico (SNII) and the Academia Mexicana de Computación (AMEXCOMP).

Fernando Martinez-Reyes is a Reader in the Engineering School at the Universidad Autónoma de Chihuahua. His research focuses on sensing and tracking technologies with applications in diverse social contexts, including health, education, agriculture, and home environments. His work examines the integration of technology into everyday life to better understand human interaction with the surrounding environment, enabling the development of context-aware services aimed at improving daily activities. His current research projects include BCIs for assistive technology development and the design of cyber-physical systems to support psychological therapy.

David Lopez-Flores received a Master of Science degree in Electronic Engineering in 2005 and a Doctor of Science degree in Electronic Engineering in 2022 from the Tecnológico Nacional de México, IT Chihuahua, where he currently works as a full-time professor. His research interests include power electronics, mechatronic systems and machine learning algorithms. He is also a member of the National System of Researchers of the Secretaría de Ciencia, Humanidades, Tecnología e Innovación (SECIHTI) in Mexico.