Proposition of a Brain-Computer Interface based on Pictograms for Communication Purpose

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***Abstract*—Brain-Computer Interface (BCI) technology enables direct communication between the brain and external devices, bypassing traditional neuromuscular pathways. This study presents a pictogram-based BCI designed to address the communication needs of patients with Amyotrophic Lateral Sclerosis (ALS) through a hierarchical menu architecture. A preliminary evaluation involving five able-bodied participants was conducted to assess the system's performance. The results demonstrate the feasibility of the proposed BCI as a functional Augmentative and Alternative Communication (AAC) tool. Although the current framework appears viable, further optimization regarding usability and interaction efficiency is required to ensure its effectiveness in the target clinical population.**

***Keywords*-brain-computer interface (BCI); assistive technology; event-related potential (ERP); augmentative and alternative communication (AAC); pictogram.**

I. Introduction

Brain-Computer Interfaces (BCIs) represent a specialized class of assistive technology that facilitates interaction through the exclusive modulation of neural signals [1]. The primary objective of these systems is to enhance the user's autonomy within their environment [2]. In cases of neurodegenerative conditions such as Amyotrophic Lateral Sclerosis (ALS), conventional assistive devices —such as voice recognition and eye-tracking— often prove inadequate due to the severe impairment of muscular and ocular functions [3]. Consequently, for individuals facing profound motor limitations, BCIs emerge as a critical alternative by circumventing the requirement for neuromuscular pathways.

In these instances, BCIs provide a robust alternative by decoding Electroencephalographic (EEG) activity to re-establish functional interaction [3]. One of the most effective EEG-based methods is the use of Event-Related Potentials (ERPs), which correspond to brain responses elicited by attended stimuli [4].

A BCI speller is a typical brain-computer interface system for communication purposes. This technology can provide users with severe motor disabilities, such as patients with ALS, with an assistive device controlled by brain activity.

Most BCI spellers are based on the P300 ERP. The P300 signal is a positive voltage deflection occurring approximately 300 ms after an infrequent or significant stimulus is perceived [5]. The P300 amplitude typically ranges between 2–5 μV and is symmetrically distributed around central scalp areas, showing greater amplitude in occipital than in frontal regions [6]. Most of these spellers are based on the P300 speller first developed by Farwell and Donchin [5]. In this BCI, a 6×6 matrix of letters arranged in rows and columns is presented to the user. The user focuses attention on the matrix element he or she wishes to select while each row and column is flashed, or intensified, randomly. After a number of flashes, the symbol that the system identifies as the intended target is presented on the screen. This paradigm is known as the Row–Column Paradigm (RCP).

Augmentative and Alternative Communication (AAC) systems empower individuals with severe speech and motor impairments by facilitating interaction through selection-based visual interfaces [7]. Specifically, pictogram-based AAC frameworks have been shown to optimize communication efficiency and enhance overall accessibility [8].

In this study, we introduce a preliminary pictogram-based AAC framework specifically engineered to facilitate communication for individuals with profound motor impairments. The proposed system aims to enhance daily communicative autonomy and, consequently, improve the overall quality of life of this population. By leveraging intuitive visual representations, the architecture seeks to reduce cognitive load while maintaining high functional utility in real-world interaction scenarios. The main contribution of this work is the preliminary design and evaluation of a configurable

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pictogram-based ERP-BCI for AAC, intended to support functional communication through the selection of meaningful pictograms rather than conventional letter-by-letter spelling. Specifically, we hypothesized that, in this preliminary evaluation with able-bodied users, participants would achieve adequate online performance and efficient message composition through the selection of pictograms.

This paper is organized as follows: Section II describes the experimental setup and presents details about the proposed AAC system. The results and discussion are presented in Sections III and IV, respectively, followed by the conclusion and future work in Section V.

II. Methods

A. Participants

Five healthy university students (aged 18.20 ± 0.45 years; 3 females, 2 males; referred to as SU01–SU05) participated in this study. None of them had previous experience using a BCI system. The study was approved by the Ethics Committee of the University of Malaga and met the ethical standards of the Declaration of Helsinki. According to self-reports, all participants had no history of neurological or psychiatric illness and had normal or corrected-to-normal vision. Written informed consent was obtained from all participants prior to data collection.

B. Data Acquisition and Signal Processing

The EEG was recorded at a sample rate of 250 Hz using the electrode positions: Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8, according to the 10/20 international system. All channels were referenced to the left mastoid and grounded to position AFz. Signals were amplified by an acti-CHamp amplifier (Brain Products GmbH, Munich, Germany).

EEG data acquisition and signal processing were managed via the UMA BCI Speller software [9], an open-source tool developed by the UMA-BCI group [10]. Built upon the established BCI2000 platform [11], this software provides a streamlined interface that simplifies complex system configurations. Signal classification was executed using a step-wise linear discriminant analysis (SWLDA) classifier, adhering to the methodology implemented in the BCI2000 P300Classifier module. This approach facilitates the customization of classifier parameters for each participant, thereby ensuring optimized performance during real-time (online) operation.

C. Proposed system

The proposed AAC system is specifically designed for individuals with severe motor impairments, including those unable to utilize muscle-based communication channels such as speech. Configured via the UMA-BCI Speller tool [9], the system allows for precise adaptation to individual user requirements. While the current implementation is tailored for Spanish-speaking users, the architecture is language-agnostic and can be reconfigured for any language.

The interface layout, menu options, and pictogram selection were defined and validated by clinical experts from the ALS Center at Hôpital Pellegrin de Bordeaux, leveraging their extensive experience with this patient demographic.

The pictograms used in the proposed system were obtained from the ARASAAC database (Centro Aragonés para la Comunicación Aumentativa y Alternativa) [12] and were selected for their relevance in AAC contexts. The selection of these pictograms ensures consistency with established clinical and educational practices for non-verbal communication systems.

Communication is facilitated through the sequential selection of pictograms organized within a hierarchical menu architecture (Figure 1). Each submenu integrates control functions to optimize user flow, including navigation to previous or primary menus, alert triggering, and text buffer management (deletion and validation). Furthermore, a virtual keyboard is included to enable the composition of personalized messages. The complete AAC framework comprises 18 distinct menus, designed to promote navigational fluidity and intuitive command selection while minimizing cognitive load. The main menu includes five main categories: needs ("*NECESIDADES*"), wants ("*QUIERO*"), questions ("*PREGUNTA*"), feelings and emotional states ("*SENTIMIENTOS*"), and physical states ("*ESTADO FÍSICO*"). In addition, the main menu includes two direct response options: Yes ("*SÍ*") and No ("*NO*"). These menus are shown in Figure 1.

The "+" symbol in the commands indicates that selecting the option leads to a submenu with additional commands. Following the RCP, stimuli were presented by intensifying each row and column of a 6×6 matrix. The intensification, also known as a flash, consisted of an overlay of a high-contrast, red-tinted image of a well-known face (Billie Eilish) against a white background. This stimulus selection was based on the work of [13], who demonstrated that familiar human faces with high visual contrast elicit more robust ERPs, thereby enhancing performance in attention-based BCI systems. While the number of functional pictograms varied across submenus, the 6×6 grid dimensions remained constant. Consequently, all rows and columns were flashed during the RCP cycle, including those containing empty cells. To maintain system stability, selections corresponding to empty cells triggered no state changes in the interface.

The stimulus presentation timing was defined by an intensification duration of 192 ms and an inter-stimulus interval (ISI) of 96 ms, resulting in a stimulus-onset asynchrony (SOA) of 288 ms. The number of sequences per selection was dynamically adjusted based on the calibration phase and individual user performance, as further detailed in Section II-D. To facilitate user orientation, a 4-second pre-selection pause was implemented, followed by a post-selection delay of 1472 ms to allow for visual feedback and

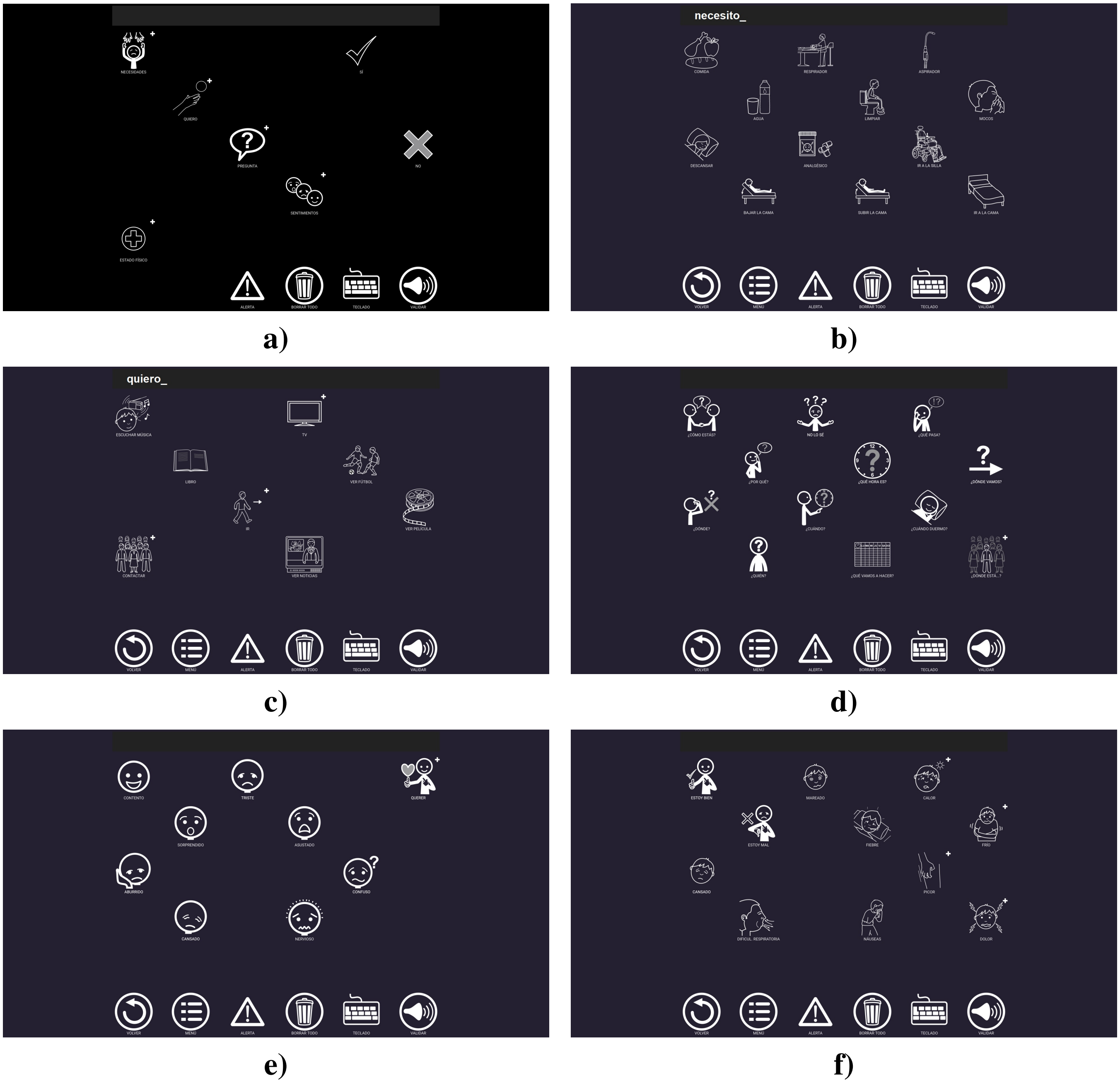

Figure 1. Overview of the pictogram-based augmentative and alternative communication (AAC) interface operated through the event-related potential (ERP)-based brain-computer interface (BCI). The figure illustrates a) the main menu and several representative submenus used for communication and interaction, including b) needs, c) wants, d) questions, e) emotional states, and f) physical states.

gaze shifting before the subsequent trial.

In summary, the platform enables the synthesis of verbal messages through the sequential selection of pictograms. Upon final validation, the system transmits the constructed message to caregivers or family members via simultaneous Text-To-Speech (TTS) output and visual display. For example, to communicate the request “I want to watch the news,” the user navigates the hierarchy by selecting the following sequence: “want+”, “watch news”, and “validate” (Figure 2). This multimodal feedback ensures clear and effective communication in real-world environments.

D. Procedure

Each experimental session began with a detailed explanation of the protocol, followed by EEG cap placement and impedance verification. Once signal quality was confirmed, participants received standardized instructions on how to operate the system. Specifically, they were asked to attend to

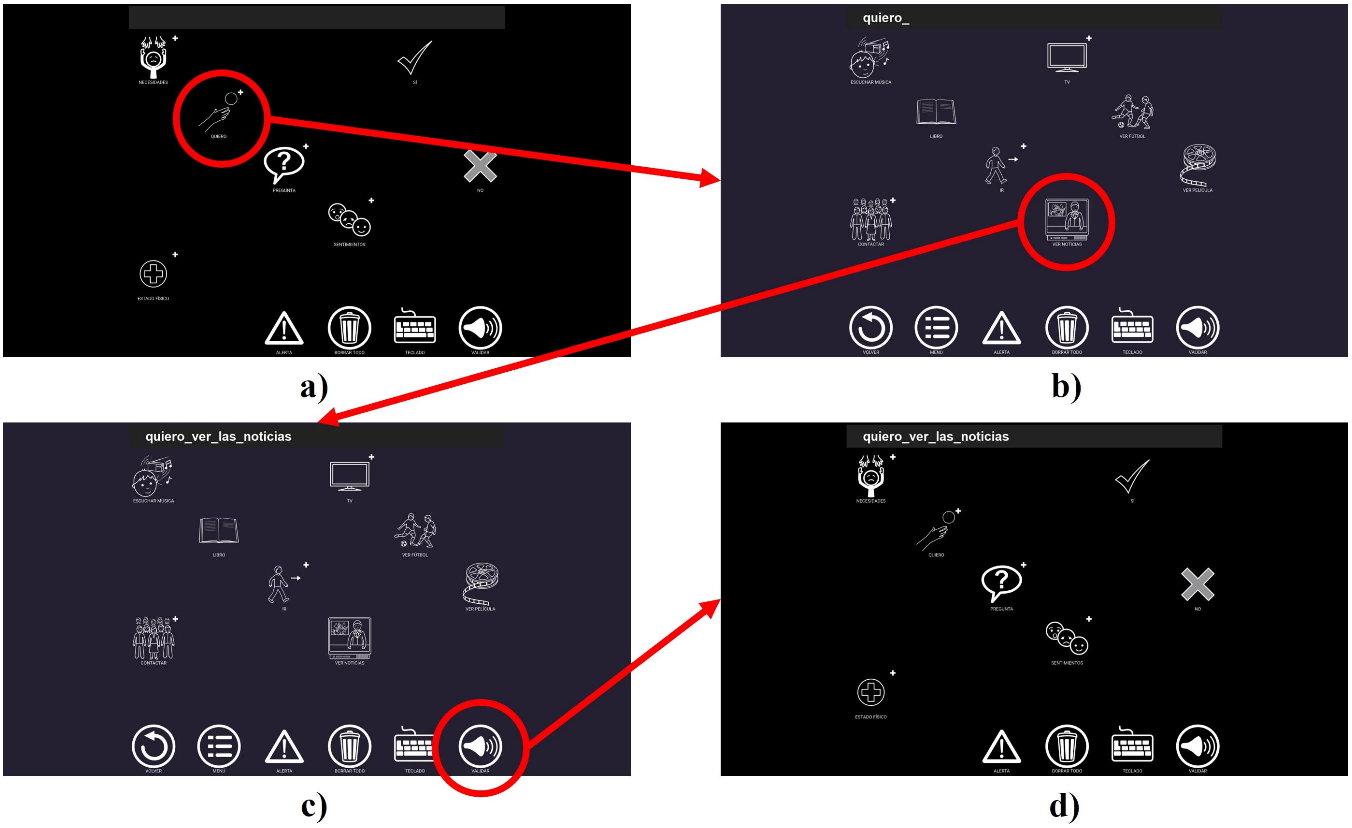

Figure 2. Examples of command selection in the proposed augmentative and alternative communication (AAC) interface for expressing the intention to watch the news: a) the user starts from the main menu and selects the *want* ("*QUIERO*") submenu; b) the specific desire to watch the news is selected ("*VER NOTICIAS*"); c) the selection is validated using the *validate* command ("*VALIDAR*") so that the command is issued; and d) the interface automatically returns to the main menu.

the desired target command within the matrix and silently count the number of times it was intensified, in order to enhance attentional engagement and promote a robust P300 response.

The interface was based on a classical 6×6 RCP. In this configuration, one stimulus sequence consisted of the sequential intensification of all 12 matrix elements (6 rows and 6 columns), resulting in 12 flashes per sequence. Although, from a theoretical standpoint, a single sequence is sufficient to determine the target coordinates, reliable P300 detection typically requires multiple repetitions to increase the Signal-to-Noise Ratio (SNR) and improve classification accuracy. Accordingly, the number of stimulus sequences was treated as an adjustable parameter and optimized depending on the experimental phase. The procedure comprised two consecutive stages: (i) an offline calibration phase and (ii) an online control phase.

1) Calibration phase: Calibration was performed using a dedicated calibration menu consisting of a 6×6 alphanumeric matrix (letters and digits) superimposed with pictograms (Figure 3). This layout was intentionally designed to resemble the final AAC interface in order to maintain visual consistency and reduce contextual changes between calibration and online use.

Participants were instructed to spell three predefined Spanish four-letter words: *GUAY*, *TREN*, and *FILO*. The number of stimulus sequences was fixed at five during calibration. Consequently, each target item was intensified 10 times (5 row flashes and 5 column flashes). The total time required to complete a single selection was 22.752 s. This duration was determined by an SOA of 288 ms applied to 12 flashes across five sequences (17.28 s), plus a 4 s pre-selection interval and a 1.472 s post-selection interval.

After data acquisition, a subject-specific P300 classifier was computed using Stepwise Linear Discriminant Analysis (SWLDA). Model performance was estimated by means of a three-fold cross-validation procedure. Based on the resulting accuracy values, the number of stimulus sequences to be used during the online phase was individualized for each participant. Sequence optimization followed a performance-maximization criterion. First, classification accuracy was evaluated using a maximum of five sequences. If 100% accuracy was achieved at this level, a retrospective analysis was conducted to determine the minimum number of sequences required to maintain perfect performance. If ceiling accuracy was not reached within five sequences, the configuration yielding the highest accuracy at this maximum length was retained for the online session. In all cases, the minimum number of sequences was set to three. This adaptive procedure sought to balance classification reliability and communication speed.

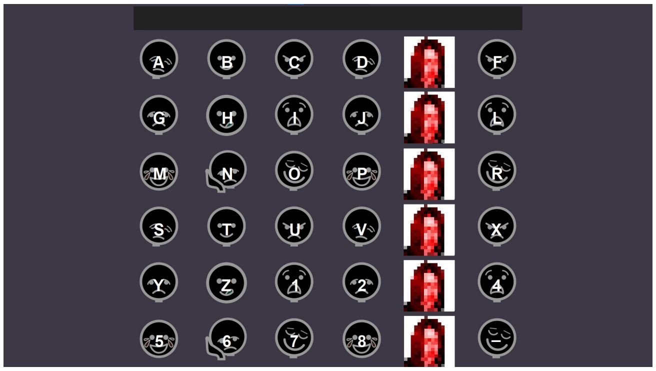

Figure 3. Interface used during the calibration task. The highlighted fifth column illustrates the stimulation mechanism of the row-column paradigm (RCP), in which entire rows and columns of the matrix are sequentially intensified. The face stimulus shown in the figure has been pixelated for copyright reasons.

2) Online phase: Prior to initiating BCI-based control, participants were allowed to freely explore the AAC interface using a conventional computer mouse. This familiarization period ensured that users understood the system structure, available commands, and menu navigation logic without the cognitive demands imposed by BCI operation.

Once participants reported being comfortable with the interface, they were instructed to prepare three independent command sets. Each set consisted of six consecutive command selections (18 commands in total) to be completed exclusively through BCI control and without interruption. Participants were free to determine the semantic content of each set, provided that it could be generated using the available AAC commands. If a selection error occurred, participants were required to correct it and continue the sequence until the intended six-command set was successfully completed. Between command sets, the system was paused to allow rest periods and minimize fatigue. This design aimed to emulate realistic AAC use while maintaining experimental control over task structure and workload.

III. Results

A. Calibration phase

The classification accuracy as a function of the number of stimulus sequences is shown in Table I. Overall, calibration performance was high. Four out of five participants (SU01, SU02, SU04, and SU05) achieved 100% accuracy. For these participants, ceiling performance was reached with three stimulus sequences or fewer, indicating robust P300 responses that enabled reliable target detection with a reduced number of repetitions. Notably, SU04 and SU05 achieved 100% accuracy from the first sequence. In contrast, participant SU03 did not reach 100% accuracy during calibration. Although performance varied across sequences, the maximum accuracy obtained was 91.67% using five sequences. According to the predefined selection criterion for the online phase, the mean number of stimulus sequences chosen per participant was 3.40 $\pm$ 0.89. For all participants except SU03, three sequences were sufficient to ensure near-perfect or perfect performance. Participant SU03 required five sequences and did not achieve ceiling accuracy.

B. Online phase

Table II summarizes the online performance during the BCI-AAC control phase. Overall accuracy remained high during real-time operation, with a mean accuracy of 95.84%. Two participants (SU01 and SU05) achieved 100% online accuracy, with no false positives (FP) or false negatives (FN). Participants SU03 and SU04 showed minor performance reductions compared to calibration, with one false negative each, while SU02 presented one false positive and one false negative, resulting in 90% accuracy. Importantly, despite the reduced number of sequences for most users (3.40 $\pm$ 0.89), classification accuracy remained above 90% in all cases, supporting the robustness of the ERP-BCI system in a realistic AAC control scenario.

The mean task completion time to execute the 18 commands was 319.51 s. As expected, participant SU03, who required five sequences, showed the longest completion time (409.54 s), illustrating the well-known trade-off between speed and accuracy in P300-based BCIs. Participants operating with three sequences completed the task substantially faster (mean $\approx$ 297 s), demonstrating that reducing the number of repetitions can significantly improve communication rate without severely compromising accuracy.

IV. Discussion

The present results suggest that the proposed ERP-based BCI system enables reliable control of an AAC interface, achieving high online accuracy (95.84 $\pm$ 4.24%) with low inter-user variability. In addition, the proposed system offers an extensive and flexible set of commands, which can be easily configured using the UMA BCI Speller software [9].

In conventional letter-by-letter AAC systems, conveying a complete message (e.g., expressing a need) typically requires multiple selections, making communication slower than when using nested pictograms. Recent advances in text prediction and generative Artificial Intelligence (AI) have already been incorporated into speller-based systems to enhance communication speed and efficiency [14]. In contrast, although some recent work has begun to explore the integration of predictive or AI-based language support into AAC systems beyond traditional spellers [8], its application to pictogram-based ERP-BCI interfaces remains limited.

TABLE I. CALIBRATION ACCURACY (%) AS A FUNCTION OF THE NUMBER OF STIMULUS SEQUENCES FOR EACH PARTICIPANT, INCLUDING THE MEAN ± STANDARD DEVIATION (SD).

Participant	Sequences				
	1	2	3	4	5
SU01	66.67	100.00	100.00	100.00	100.00
SU02	33.33	75.00	100.00	100.00	100.00
SU03	58.33	91.67	83.33	75.00	91.67
SU04	100.00	100.00	100.00	100.00	100.00
SU05	100.00	100.00	100.00	100.00	100.00
Mean ± SD	71.66 ± 28.63	91.33 ± 12.10	96.67 ± 7.46	95.00 ± 11.18	98.33 ± 3.73

TABLE II. ONLINE PERFORMANCE RESULTS FOR EACH PARTICIPANT, INCLUDING THE MEAN ± STANDARD DEVIATION (SD), DURING THE ONLINE PHASE. TRUE POSITIVES (TP) CORRESPOND TO CORRECTLY SELECTED TARGET COMMANDS; FALSE POSITIVES (FP) CORRESPOND TO SELECTIONS OF NON-TARGET COMMANDS; FALSE NEGATIVES (FN) CORRESPOND TO TRIALS IN WHICH AN EMPTY CELL (I.E., A CELL WITHOUT AN ASSOCIATED COMMAND) WAS SELECTED, RESULTING IN NO EXECUTED COMMAND DESPITE AN INTENDED TARGET.

User	Sequences	TP	FP	FN	Accuracy (%)	Time (s)
SU01	3	18	0	0	100.00	285.12
SU02	3	18	1	1	90.00	316.80
SU03	5	17	0	1	94.44	409.54
SU04	3	18	0	1	94.74	300.96
SU05	3	18	0	0	100.00	285.12
Mean ± SD	3.40 ± 0.89	17.80 ± 0.45	0.20 ± 0.45	0.60 ± 0.55	95.84 ± 4.24	319.51 ± 52.01

Extending generative and predictive strategies to pictogram-driven AAC systems could substantially improve message construction efficiency while preserving the advantages of symbolic communication.

Nevertheless, the present findings should be considered preliminary, as the sample included only five participants without severe motor impairments. Therefore, the results cannot be directly generalized to users with severe motor disabilities, who may face additional challenges related to fatigue, attention, visual control, and prolonged use. Future work should involve testing the system with this population, in collaboration with clinical professionals, relatives, and caregivers, to evaluate its usability, communication efficiency, and required adaptations.

V. CONCLUSIONS

This study demonstrates the feasibility of controlling a flexible and customizable pictogram-based AAC interface through an ERP-based BCI with high reliability. The proposed system, defined and validated by clinical experts from the ALS Center at Hôpital Pellegrin de Bordeaux, provides a wide and configurable set of commands, allowing users to construct meaningful messages beyond simple letter-by-letter spelling. These commands can be modified and adapted to patient needs.

The high online performance observed across participants supports the robustness of the approach and its suitability for practical communication scenarios. By combining symbolic communication with BCI control, the system represents a promising step toward more functional and user-centered assistive communication solutions.

Future work should focus on validating the system with end users presenting severe motor impairments and assessing its long-term usability in real-world environments.

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