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Brain-computer interface (BCI)-generated speech to control domotic devices

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A B S T R A C T

A brain-computer interface (BCI) is a type of technology that establishes a communication channel between a user and certain devices in the environment via the brain signals of the user. The UMA-BCI Speller tool allows for easy configuration of a BCI, permitting it to be manipulated without the need for much technical knowledge. However, adapting a BCI system so that it can communicate with devices is a challenging task. A simpler technology that is increasingly used to enable communication with devices in the environment is based on voice commands. The aim of the present work is therefore to create a system to facilitate communication between a BCI and devices in the environment using voice commands. Twelve healthy participants and three amyotrophic lateral sclerosis (ALS) patients were asked to control a BCI home automation system. The devices to be controlled were a television, an air conditioner, a smart light bulb, a smart plug, and the WhatsApp and Spotify apps. Performance measures were recorded, and subjective measures were collected based on the System usability scale, NASA-TLX and ad hoc questionnaires. The results of this study validate the proposed system as a suitable option to facilitate communication between a BCI and commercial devices that have been previously adapted to operate based on voice commands.

1. Introduction

A brain-computer interface (BCI) is a type of technology in which the brain signal of a user is exploited to establish a communication and control channel between the user and an external device [1,2]. The main advantage of these systems is that they do not require muscular control for management, meaning that this technology may be a suitable option for people who have lost the ability to move their muscles, as in some cases of Duchenne muscular dystrophy (DMD) or amyotrophic lateral sclerosis (ALS) [3,4]. The neuroimaging technique most commonly used by BCIs is electroencephalography (EEG), possibly due to its portability, relatively low cost and high temporal resolution [5]. The present work therefore focuses on the use of EEG as an input signal of a BCI system.

There are several well-known EEG signals that are frequently used to control BCIs, and these can be divided into endogenous and exogenous signals. Endogenous signals are based on the self-regulation of the EEG in the absence of external stimuli, and the most commonly used are sensorimotor rhythms (SMR) elicited by motor imagery (MI) tasks. Exogenous signals are elicited by an external stimulus; the most frequently used are steady-state evoked potentials (SSEPs) and event-related potentials (ERPs). SSEPs represent steady-state responses to periodic stimuli, such as steady-state visual evoked potentials (SSVEPs) and auditory steady-state responses (ASSRs). In contrast, ERPs are changes in the EEG signal that are elicited as a response to a specific external event. Events that trigger an ERP may have various different modalities, such as visual, auditory, or tactile stimuli. In cases where the user has not lost the ability to control the visual channel, BCI systems based on visual ERPs have generally shown the best performance and have the highest number of available commands [5–7]. In addition, these systems have shown promising results for users with severe muscle control problems, such as patients affected by ALS or DMS [8,9] or even for patients in a locked-in state, as shown in [10]. Visual ERPs were therefore selected as the input signal in this work to establish a communication channel between these patients and their environment.

Visual ERPs are some of the most frequently used signals by BCI devices. The review in [7] noted that 65 % of the BCI spellers analyzed used ERP signals. There are numerous types of ERPs that are evoked by different events. Some of the most commonly used in the visual modality are N200 and P300 (e.g., [11,12]); both of these

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are triggered by the appearance of a desired stimulus but vary in terms of their shape and spatiotemporal location in the cerebral cortex. N200 is a negative potential located in the parieto-occipital region, which appears 200–350 ms after the onset of the desired stimulus [13], while P300 is a positive potential located along the central line in the parieto-occipital region, which appears around 300–550 ms after the onset of the stimulus [14]. These ERPs are typically evoked through an oddball paradigm, in which a set of visual stimuli are pseudo-randomly presented while the user pays attention only to one of them, thus resulting in an ERP after the stimulation the attended (or target) stimulus. The objective of these BCI systems is to detect ERPs associated with the presentation of the target stimulus, which has an associated control command. In order to achieve this, the system averages the resulting EEG signals after a predetermined number of sequences (i.e., the presentation of all available stimuli), and identifies the item the user wanted to select. These systems usually need to be calibrated in order to recognise users' specific ERPs and to be able to discriminate between (i.e., classify) target and non-target stimuli.

EEG-based BCI applications presented in previous works have been extensive, and have been developed for the control of various devices, such as a wheelchair (e.g., [15]), a speller (e.g., [16]) or a domotic system (e.g., [17]). The present work focuses on the last of these. Domotic control can provide autonomy to patients who are unable to interact with their environment, and who depend on caregivers for daily tasks. Table 1 lists the EEG-BCI studies that, to our knowledge, have presented detailed reports of systems related to domotic control. It can be seen that three out of nine papers used visual ERPs as control signals. The devices of interest included a TV, a light bulb and an air conditioner.

The schemes in Table 1 were designed to enable control of several devices commonly found in patients' homes. However, most of the systems used in these works suffer from a major drawback in terms of real-world use in patients' homes, as it is necessary to configure the communication channel between the BCI system and the intended devices. Since BCI systems are not a widely used technology, it is highly unlikely that the devices are commercialised with a configuration that allows them to be controlled by a BCI. Hence, in order to establish a communication channel between the BCI system and the device, specific technical skills would be required (e.g., programming knowledge), which the people supporting the patient (family or caregivers) do not necessarily have.

There is now a flexible and mature technology for the general public (i.e., non-patients) that allows for control of commercial devices in a straightforward way. This type of technology relies on voice control via a virtual assistant, which interprets the commands given by the user. Some of the most commonly used virtual assistants are Alexa, Siri, Cortana and Google Assistant [26]. In other words, control via voice assistant is a much more widespread technology than direct control via a BCI. It may therefore be desirable to use a BCI system to create voice commands that can be interpreted by a virtual assistant.

To our knowledge, this idea of bridging communication between the BCI system and other devices (or applications) through voice commands has previously been employed in only two works. In [27], a BCI messaging system was created to control Whatsapp, Telegram, an email client and an SMS system via UMA-BCI Speller and Google Assistant. UMA-BCI Speller is easily configurable software that uses a visual ERP signal and allows for flexibility in terms of creating the graphical user interface, navigating between menus and freely constructing the desired voice commands [28]. However, since this approach did not aim to control external devices but mobile messaging systems, it cannot be considered a domotic system. In contrast, the scheme in [21] did aim to control external devices of the environment system via an ASSR signal. Specifically, this work used a voice assistant (Alexa) to control two devices: a light bulb and a fan. The connection with the devices was made through an OpenBCI system using a primary Arduino interface with a proximity sensor, a secondary Arduino board with a secure digital (SD) card module communicating serially with the EEG processing integrated development environment (IDE) and a voice-controlled device. The primary drawback of this system was that in order to adapt it to new devices, programming skills would be required to manipulate the EEG processing IDE and to modify the emitted voice messages. It would therefore be interesting to develop a BCI system that can be easily configured by caregivers, who could then adapt the domotic devices that would be controlled by the patient, based on his/her needs and preferences, without the need for technical knowledge. This flexibility could be provided by the previously mentioned UMA-BCI Speller software. This could be exploited to generate voice commands to control a domotic system. In short, the aim of this work is to present a flexible domotic control system that can be adapted to the devices and applications that the user wishes to control. To the best of our knowledge, this is the first work in the area of BCIs to propose domotic control of several devices and applications using voice commands and an easily configurable BCI that can be manipulated by non-technical users. The main advantage of the proposed system is that after proper configuration of the different menus in the BCI software (UMA-BCI Speller), it allows for control over any devices and applications that have been previously configured to be controlled through voice commands by a virtual assistant (Google Assistant).

Table 1
EEG-based BCI proposals that include daily use systems.

Work	EEG signal	Controlled devices
[18]	Visual ERP	TV, DVD player, hi-fi system, multimedia hard drive, lights, heater, fan and phone
[19]	Visual ERP	lights, doors, fan, camera, media player and predefined web sites
[17]	Conceptual imagery	Kettle, shutters, TV and light
[20]	Auditory ERP	TV, air conditioner and emergency call
[21]	ASSR	Smart bulb and fan
[22]	SSVEP	Robotic vacuum, air cleaner, and humidifier
[23]	SSVEP + temporalis muscle (EMG)	Wheelchair, nursing bed, TV, telephone, curtains and lights
[24]	SMR	Medical call, service call, catering ordering, TV and two air conditioners (wall-hanging and cabinet)
[25]	Visual ERP	TV, air conditioner and emergency call

Note: EEG, electroencephalography; ERP, event-related potential; ASSR, auditory steady-state responses; SSVEP, steady-state visual evoked potentials; EMG, electromyography; SMR, sensorimotor rhythms.

2. Materials and methods

2.1. Participants

The present study involved 12 healthy voluntary participants (aged 23.5 ± 6.07 years, eight male and four females, referred to here as *H*01–H12) and three patients (aged 68 ± 9 years, two male and one female, referred to as P01–P03). All three patients were affected by ALS (Table 2). H08–*H*10, P01 and P03 had participated in a previous experiment, and therefore had experience in controlling a visual ERP-based BCI. The study was approved by the Ethics Committee of the University of Malaga, and met the ethical standards of the Helsinki Declaration. All participants provided written consent. According to self-reports, none of the participants had any history of psychiatric or neurological illness (except ALS in the case

Table 2
Patients' information.

Patient	Gender	Age (years)	Years post-diagnosis	ALSFRS-R score	Communication method
P01	male	77	9	21	Hands, arms, facial gestures and head movements
P02	female	68	2	7	Facial gestures and head movements
P03	male	59	7	0	Winks and eye movements

Note: ALSFRS-R stands for Revised ALS Functional Rating Scale [29].

of the patients). Healthy participants received a monetary remuneration of 5€.

2.2. Data acquisition and signal processing

The EEG was recorded at a sample rate of 250 Hz using the electrode positions: Fz, Cz, Pz, Oz, *P*3, *P*4, PO7 and PO8, according to the 10/10 international system. These electrode positions have been commonly used in previous literature related to visual ERP-BCI (e.g., [18,30] or [31]). All channels were referenced to the left mastoid and grounded to position AFz. Signals were amplified by an acti-CHamp amplifier (Brain Products GmbH, Gilching, Germany). All aspects of the EEG data collection and processing were controlled by the BCI2000 system [32]. No artifact detection or correction techniques were applied.

The type of EEG signal used to control the BCI was visual ERPs. ERP-based paradigms require a calibration phase in order to obtain the subject-dependent parameters for online experiments. These subject-dependent parameters consist of the weights for the classifier that is applied to the EEG signal to determine the item focused on by the participants. To obtain the weights, a stepwise linear discriminant analysis (SWLDA) was carried out on the calibration data – 12 trials in which the user must focus his/her attention on the element indicated by the interface, as described in section 2.5 Procedure – using a BCI2000 tool called P300Classifier. The use of SWLDA is because the UMA-BCI Speller tool, as it is a wrapper of BCI2000, also uses the P300Classifier tool, which by default uses this algorithm. A detailed explanation of the SWLDA algorithm can be found in the P300Classifier user manual [33], where it is summarized as a process "to obtain a final linear model that approximately fits a set of data (stimulus) by using multiple linear regressions and iterative statistical procedures, thus selecting only significant variables that are included in the final regression". The default configuration was used (60 as maximum number of features to be kept in the SWLDA algorithm, and 0.1 and 0.15 as maximum *p*-value for the respective inclusion or exclusion of a variable in the model). SWLDA analyses a time interval after the presentation of a stimulus in order to obtain the mentioned variables (the weights of the classifier); the default time frame (widely used for visual P300) is 0–800 ms.

2.3. System implementation

The aim of the BCI system was to generate voice commands that could be interpreted by a virtual assistant. These voice commands were intended to control various applications or devices. A laptop (HP Envy 15-j100, 2.20 GHz, 16 GB, Windows 10) was used to run the software that presented the stimuli and registered and analyzed the EEG signal. This software was UMA-BCI Speller (version 0.45, May 2021) [28], a free tool that wraps BCI2000 and simplifies its configuration and control, and which was used to spell out the text and convert it into voice commands. A virtual assistant (Google Assistant) running on a smartphone (Samsung Galaxy A51 with Android 11) received and interpreted the voice commands sent by UMA-BCI Speller and performed the corresponding action. The structure of the system is illustrated in Fig. 1.

In the following, we describe the different applications and devices that were controlled via the implemented BCI system. Google Assistant was able to directly control WhatsApp to send messages and Spotify to play music. It was also possible to communicate directly with the assistant to make specific requests (e.g., to set an alarm for 9:00 or to ask whether it was going to rain the next day). Google Assistant communicated with the different devices through a Wi-Fi connection, including a smart light bulb, a radio receiver controlled via a smart plug, a Google Nest device, and an infrared emitting controller ("Universal Remote RM4 mini") that managed two other devices. In the laboratory, the devices handled by healthy participants via the infrared controller were a TV (Blusens H.93-19P-SP) and an air conditioner (Haier). It was necessary to use this type of controller because these devices did not allow for control via Wi-Fi. In the patient trials, which were conducted in the patients' homes, air conditioning was not present, and the TV was the one owned and commonly used by them at home; this did not present a problem, since the infrared system could easily be adapted to handle this device. The infrared controller received the commands from Google Assistant via Wi-Fi and emulated a conventional remote control. Each of the different options allowed by the system are detailed in Section 2.4 below.

To avoid ambient noise affecting the understanding of the command by the virtual assistant (which would worsen the performance), the voice commands from UMA-BCI Speller were sent to the smartphone via a cable connection (using a standard mini-jack audio cable) between the laptop audio output and the microphone input to the smartphone. The output volume of the laptop remained fixed throughout the experiment, so that the assistant always received the same level of audio. The Windows 10 Narrator (a text-to-speech feature) was used with the "Microsoft Helena" option from the Spanish voice catalogue. Since the voice commands were generated using a synthesized voice, the assistant was expected to interpret the same commands in the same way. However, as detailed below in Section 3.1.2, this was not always the case. As the virtual assistant used in the experiment was Google Assistant, each command started with the words "*OK Google*...", which is one of the wake-up phrases for the assistant. In order to present feedback to the user, the voice commands sent by UMA-BCI Speller were played over a set of speakers. The responses from Google Assistant and the music from Spotify were played on another set of speakers.

2.4. Control paradigm

With the aim of easing the understanding of the control paradigm, a video showing two example actions is provided as supplementary material.

In order to send a control command to the virtual assistant, users had to select items from different menus. The selection of an item followed the usual procedure based on an ERP row-column paradigm (RCP): users needed to pay attention to the desired item (from a matrix of possible items) and mentally count the number of times that it was highlighted. The stimulation of these items was done in groups of rows or columns of the matrix, using images that were superimposed on all the items of the high-

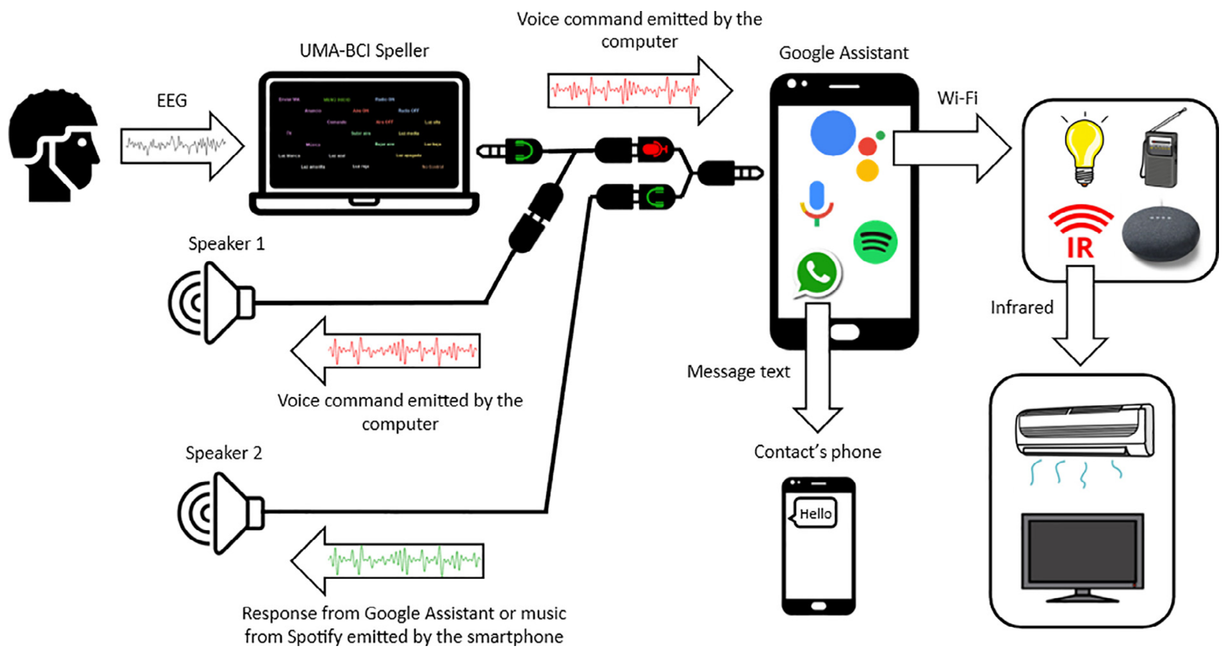

Fig. 1. System implementation. An oddball paradigm allows the user to select items from a matrix to build the text that will be converted to a voice command (e.g., "*OK Google, turn on the air conditioner*"). This voice command is sent to one loudspeaker and to the microphone input of the smartphone. The smartphone virtual assistant receives the voice command from the computer, performs the corresponding action, and gives an audio response to the user (e.g., "*OK, I turned on the air conditioner*") through a different loudspeaker.

lighted row or column. The timing of each selection was the same for all the menus, as all the interfaces consisted of a 7 × 7 matrix, although three of them contained dummy items (i.e., items that had no associated command and therefore had no effect when selected). The dummy items were of two types: non-visible and visible items (a letter "X" over which an image appeared). The non-visible dummy items were used for two reasons: (i) all of the menus needed to have a matrix of equal size for UMA-BCI Speller to work properly, so the size had to be matched to the larger menu size, and (ii) this improved the security of the system, since if the row or column of the target item was not correctly detected, it was likely that a dummy command would be selected instead. From the user's point of view, this wrong selection of a dummy command would result in a false negative (since he/she wanted to select an item that would cause a change, but the system had offered no response), which entailed fewer problems than the execution of a false positive (as the selection of an incorrect command may require the selection of another command to correct it). The use of visible dummy elements in the interface was also intended to reduce the salience of the non-target stimulus that did have a command associated with it. The number of visible dummy items in some menus was selected to ensure that these menus had approximately the same number of visible items as the start menu (20 items, see Fig. 2). An item was selected after all seven rows and columns had been highlighted a certain number of times (this is explained further in Section 2.5).

Several menus were implemented to allow subjects to form a sentence that would finally be converted to speech by the Windows 10 Narrator voice synthesizer (in the following, this conversion will be referred to as "speaking"). The commands were constructed by selecting items from the interface, and could be built in two different ways: (i) through the selection of a single item from the interface (e.g., selecting the item "Radio ON" to turn on the radio by writing directly "*OK_Google._Turn_on_the_radio*"), or (ii) gradually in a series of steps (e.g., first selecting the item "Music" to access the music menu and then choosing a specific musical genre, e.g., Rock, to create the phrase "*OK_Google._Play rock music*"). In other cases, the user was allowed to make a letter-by-letter selection, enabling maximum flexibility to send some specific commands not previously determined by the interface (e.g., after selecting the music menu and the option of a specific song, the user had to manually type the name of that song).

As mentioned above, the UMA-BCI Speller was used for stimuli presentation and menu navigation. Six menus were implemented as shown in Fig. 2.

a. No control (NC) menu (Fig. 2a). This was a 7 × 7 matrix in which only one item was a valid command ("IC"), and there were 29 non-visible and 19 visible dummy items ("X"). The objective of this menu was to allow subjects to remain in a state where they could rest without generating control commands; the term "no control" is generally used in asynchronous systems to refer to such a state. The only valid command was "IC" ("intentional control", located in the centre of the interface), and selecting this item loaded the Start menu. The probability of unintentionally selecting this item and thus changing the menu was 1/49 ≅ 2 %. No voice command was generated in this interface.
b. Start menu (Fig. 2b). This was the main menu for the system, which allowed participants to choose the application or device they wanted to use. There were 20 live items, and the remaining 29 options were non-visible dummy items. The 20 live items could be grouped into nine categories:
- Send WA. This item opened the spelling menu (Fig. 2e, explained in more detail in point e), which allowed the user to select a contact and send a message through the WhatsApp messaging application, and to choose the spelling of the message itself.
- Announcement. This item opened the spelling menu, which allowed an announcement to be written and sent to the Google Nest device at a remote location from where the participant was. This option could be useful in a real-world setting to allow patients to send a message to caregivers in another room.

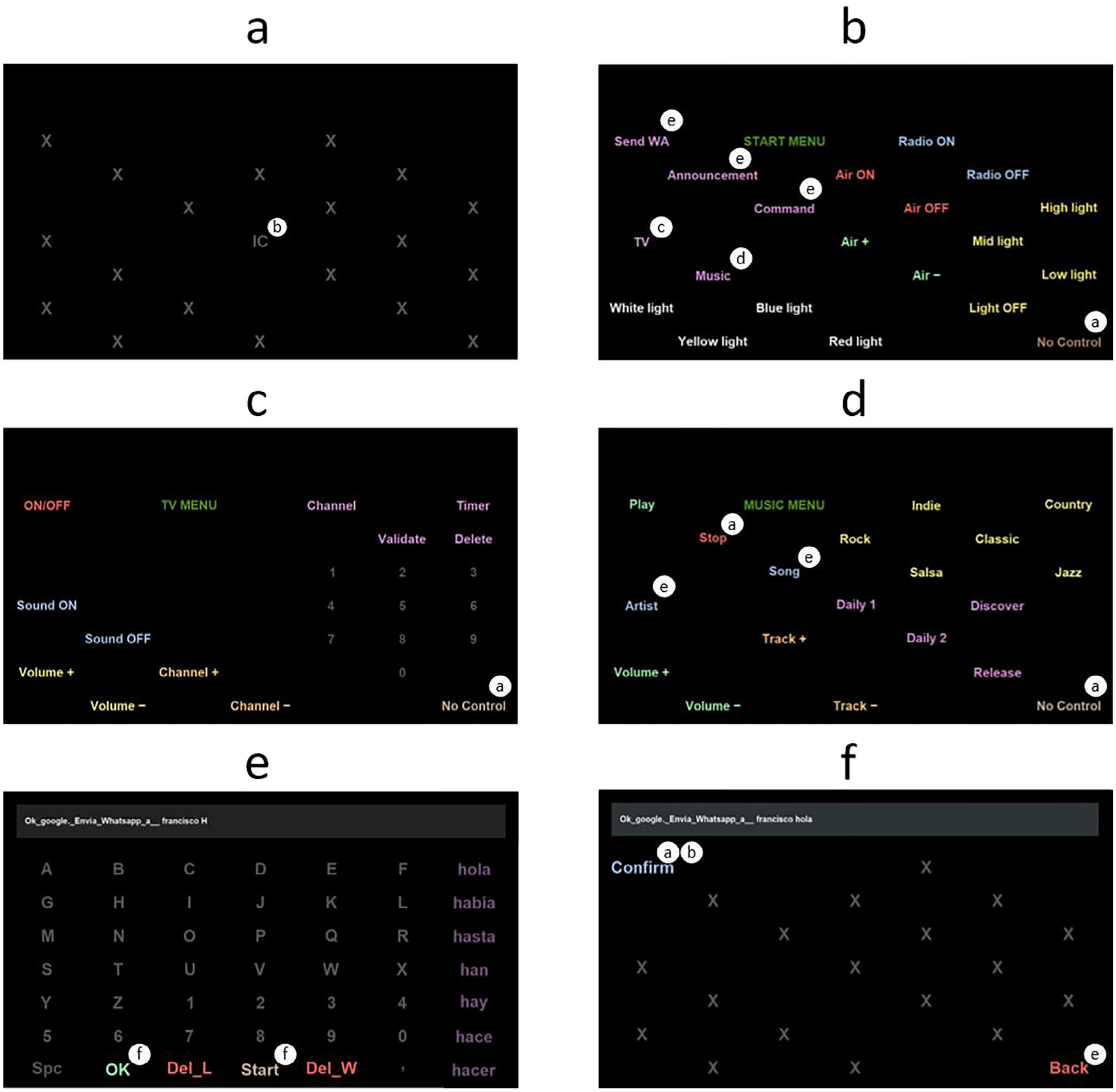

Fig. 2. Navigation via the six available menus: (a) no control, (b) start menu, (c) TV, (d) music, (e) spelling, and (f) confirmation. A letter within a white circle represents a change to a different menu. The images shown in this figure are English translations of the original Spanish commands.

– Command. This item opened the spelling menu, which allowed the participant to type and send a free voice message to the Google Assistant in order to solve a question or send a command (e.g., "*Is it going to rain today*?" or "*Tell me a recipe for a Spanish omelet*").
– TV. This opened the TV menu (Fig. 2c, explained in more detail in point c), which allowed the user to control the television.
– Music. This opened the music menu (Fig. 2d, explained in more detail in point d), which allowed the user to control the Spotify application.
– Light. The Start menu contained several items that allowed the user to control a smart bulb. The options for this device were varying its intensity to 100 %, 50 %, 20 % and 0 % ("High light", "Mid light", "Low light" and "Light OFF", respectively) and changing the color to white, yellow, blue or red ("White light", "Yellow light", "Blue light" and "Red light", respectively).
– Air conditioner. The Start menu contained four items related to the control of an air conditioner: turning it on or off, and raising or lowering the temperature ("Air ON", "Air OFF", "Air +" and "Air –", respectively).
– Radio. The Start menu had only two commands related to radio control: turning it on or off ("Radio ON" and "Radio OFF", respectively). Only two commands were used, since the radio was controlled via a smart plug. The radio could be replaced by any other device for which the user needed to control only two states of the plug (i.e., turning it on or off).
– No control. Finally, the NC item was included in order to allow subjects to voluntarily change to the NC menu, in case they wanted to take a rest.

c. TV menu (Fig. 2c). This consisted of 22 selectable items and 27 non-visible dummy items. From this menu, it was possible to turn the TV on or off ("ON/OFF"), turn the sound on or off ("Sound ON", "Sound OFF"), increase or decrease the volume

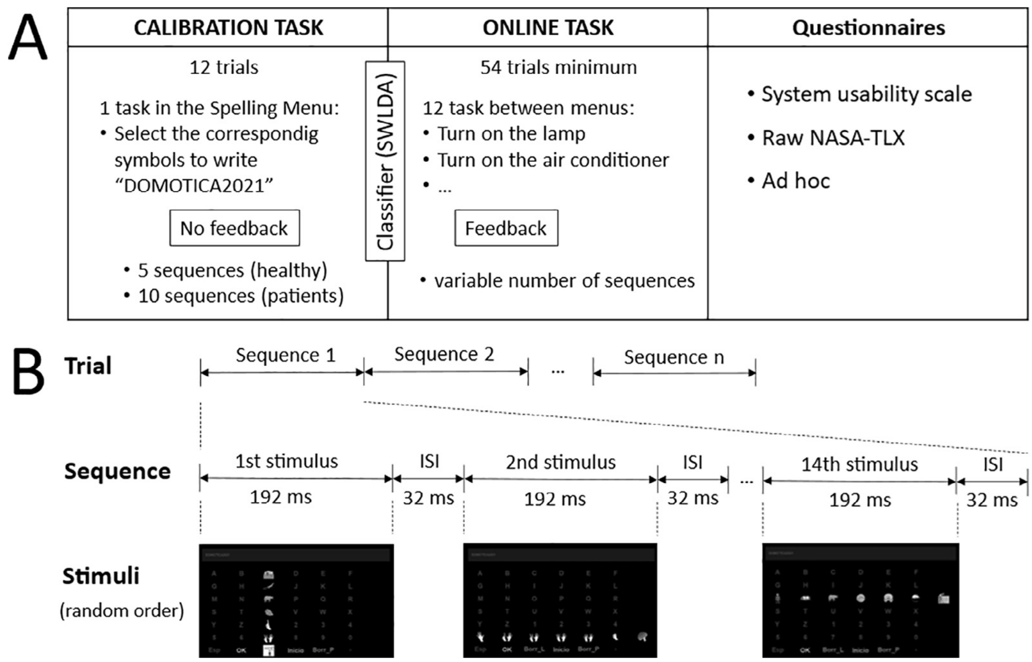

Fig. 3. (A) Summary of the procedure to be carried out by the participant. (B) Timing of a trial, including a variable number of sequences (depending on the task and the participant) and, for every sequence, the presentation of 14 stimuli for 192 ms each (7 rows + 7 columns) separated by an interstimulus interval of 32 ms.

("Volume +", "Volume –") or channel, ("Channel +" and "Channel –"), and to set a timer so that the TV would turn itself off after a certain number of minutes chosen by the user. To change to a specific channel or to set a timer, the user needed to make a series of selections: first the "Channel" or "Timer" item, and then the item corresponding to the desired number (the channel or the minutes for the timer), and finally the "Validate" item to confirm the selection. If an incorrect number was selected for the channel or the timer, the user could delete this choice using the "Delete" command. An item was also shown that allowed the user to return to the NC menu.

d. Music menu (Fig. 2d). This consisted of 19 selectable items and 30 non-visible dummy items. It allowed the user to play or stop playing music ("Play" and "Stop"), to choose a specific artist or song ("Artist" and "Song"), to change the volume ("Volume +", "Volume –"), to skip to the next or previous song ("Track +" and "Track –"), and to choose a specific playlist ("Daily 1", "Daily 2", "Release", "Discover") or genre of music ("Classic", "Indie", "Salsa", "Rock", "Country" and "Jazz"). If the user wanted to play a specific song by an artist and therefore selected the corresponding items ("Artist" and "Song", respectively), they were taken to the spelling menu to type the specific name of the song or artist they wanted to listen to. In addition to stopping the music, the command "Stop", automatically redirected the user to the NC menu. As in the TV menu, there was a specific item to allow the user return to the NC menu, which could be used to leave the current menu without stopping the music.

e. Spelling menu (Fig. 2e). This consisted of 49 selectable items and no dummy items. When users selected the items "Send WA", "Command", "Announcement", "Song" or "Artist" from the music/Spotify menu, the system changed to the Spelling menu (after adding some predetermined text, e.g., "*OK_Google._Play_in_Spotify_the_song_*[name of song]"). This menu was implemented to let the user create additional commands that were not specified in the interface (such as choosing a specific song or asking the Google Assistant what the temperature would be the next day). UMA-BCI Speller includes a text prediction function that may help users when spelling words. As users choose the characters of a word (starting with the first character), the system suggests several words based on the characters already written and the probability of occurrence, based on a Spanish-language-specific corpus. The first six columns and rows of the 7 × 7 matrix corresponded to specific characters that could be added (letters from the English alphabet and numbers). The last column was used to provide subjects with seven predicted words (presented in a different text color, as shown in Fig. 2e). The last row contained two characters ("Spc", to input a low bar used as a space, and ",'' to input a comma), two delete commands ("Del_L" to delete a single letter and "Del_W" to delete a complete word) and two control commands ("OK" to confirm the written text, and "Start", which allowed the user to return to the Start menu without generating a voice command in the case where this menu was loaded unintentionally). When the "OK" or "Start" items were selected, a confirmation menu (Fig. 2f) was presented to subjects in order to avoid accidental selections of these two commands. It should be mentioned that in the WhatsApp menu the message had to be spelled immediately after the contact, only separated by a automatically placed low bar (i.e., "*Ok_Google._Send_a_WhatsApp_to_*[*contact*]_[message]") or a space bar if the participant had used a suggested word to input the contact.

f. Confirmation menu (Fig. 2f). This was presented after the user had selected the "OK" or "Start" commands from the Spelling menu, in order to ensure that the user really wanted to perform this action. The reason for requiring confirmation was that confirming the spelling (using the "OK" command) or going back to the NC menu (using the "Start" command) would involve deleting the characters already spelled. Two valid items were shown (alongside 18 visible dummy items and 29 non-visible dummy items in a 7 × 7 matrix): the first allowed the user to validate the previous selection ("Confirm" if the previous selection was the "OK" command to validate the written text, or "Start" if the previous selection was the

"Start" command to go to the Start menu), and the second allowed the user to cancel their previous selection and return to the Spelling menu ("Back"). As explained above, the item used to validate a command was "Confirm" or "Start," depending on whether the user had previously selected the "OK" item (to send typed text) from the Spelling menu or the "Start" item (to go to the start menu), respectively. If the user confirmed an "OK" command from the Spelling menu (by selecting "Confirm" from the Confirmation menu), the system spoke (and then deleted) the complete sentence so that it could be interpreted by the virtual assistant, and then loaded the NC menu. If the user confirmed a "Start" command from the Spelling menu (by selecting "Start" from the Confirmation menu), the system deleted the written sentence and loaded the Start menu. The "Back" command could be used if the previous item ("OK" or "Start" from the Spelling menu) had been selected by mistake, and the Spelling menu was then loaded in order to allow the user to continue writing the sentence to be sent to the virtual assistant.

These menus were configured to evaluate whether the system worked correctly with the specific applications and devices that were deemed useful (TV, Whatsapp, Spotify, etc.). However, it should be noted that the UMA-BCI Speller tool is totally flexible, and that these menus could be adapted to the individual needs of the user.

To allow the reader to understand the operation of the interface control paradigm in more detail, video 1 is presented as demonstration: in this example the user chose to send a WhatsApp message to "Francisco" with the text "hola" and to play music in Spotify.

2.5. Procedure

Before starting the experiment, healthy participants watched a video (8:23 min long) giving practical details about the experimental process (including how to control the interface, navigate between menus and complete the tasks). For the patients, an explanation of how the system worked was given in person during the experimental session. The healthy participants attended the laboratory, where the experimental apparatus had been set up. However, in the case of the patients, the research staff took the entire experimental equipment needed to perform the test to the patients' homes. Once the task had been explained and the necessary instrumentation for the recording of EEG activity had been set up, an experiment was carried out that consisted of three parts for both healthy participants and patients (Fig. 3A): (i) a calibration phase, which was used to obtain the subject-dependent parameters of the EEG classifier; (ii) an online experimental phase; and (iii) a final phase in which the subjects filled out several questionnaires related to their subjective experiences in terms of controlling the interface. The duration of the session was 80–100 min for healthy participants in the laboratory, and 100–130 min for the ALS patients. For patients, this longer session time was related to (i) the time needed to set up the devices at the user's home, (ii) the explanation of the session was performed from the beginning (they did not receive the introductory explanatory video), (iii) the process of prepare the EEG instrumentation was slower and (iv) the performance was lower than that of healthy users, so they required more time to complete the required tasks. In the case of patients P01 and P03, two visits had to be made, since it was not possible to achieve adequate control of the system in the first visit.

The calibration phase involved paying attention, without feedback, to 12 predetermined items ("DOMOTICA2021") in the Spelling menu (Fig. 2e). For the healthy participants, the number of sequences (i.e., the number of times that each row and column were highlighted) was fixed at five, meaning that each item was highlighted 10 times. The duration of the stimuli was 192 ms and the stimulus onset asynchrony (SOA) was 224 ms (Fig. 3B). For the patients, 10 sequences were used, to give them a better chance of achieving adequate performance in an experimentally uncontrolled environment, such as their home. The experiments with patients required significant investment of resources and effort, so prioritizing the success of the session and the user experience over following a fixed protocol was a major concern. The calibration task lasted 5:23 min for the healthy participants and 8:31 for the patients. After the calibration step, an SWLDA analysis was performed to obtain the subject dependent P300 classifier. Based on the accuracy of the results obtained with this classifier, the number of sequences was adjusted for each subject. For healthy participants, the criterion applied to choose the number of sequences aimed to maximize the written symbol rate (WSR), as in [27,34,35]. In the same way as in [27], this criterion was adapted so that the minimum number of sequences was three. However, for the patients, the choice of the number of sequences was made subjectively, based on the one with which the user felt comfortable, as long as the accuracy was 100 % in the calibration step. To ensure that the patient was comfortable with the number of sequences chosen, at least one test was performed (consisting of writing the word "*hola*", or "*hello*" in Spanish) with the desired number of sequences, until the patient gave his or her approval. The online experimental part consisted of several tasks to be performed using different applications and devices. These tasks were displayed on two separate pages, one on each side of the screen, so the subjects could check if they had forgotten the details. These instructions explicitly set out which command had to be chosen from the interface to accomplish the given task. If the participant made a mistake (even if that mistake completed a subsequent task), he/she had to correct the selection and continue with the process. The tasks were carried out in the same order, and are listed below (the specific commands required to complete each task are shown in parentheses):

1. Start from the NC menu.
2. Go to the Start menu ("IC") and turn on the lamp to high intensity ("High light").
3. Turn on the air conditioning ("Air ON") and increase the temperature ("Air +").
4. Turn on the radio ("Radio ON") and listen to it for one minute in the NC menu ("NC"). Then turn it off ("IC", "Radio OFF").
5. Access the Command menu to enter "*tiempo hoy*" ("Command", "T", "tiempo", "H", "hoy", "OK", "Confirm"), meaning "*weather today*" in English.
6. Access the Start menu ("IC"), and then the Music menu ("Music"). Choose a free genre (e.g., "Jazz"), increase the volume ("Volume +"), select the next song ("Track +") and go to the NC menu ("No control").
7. Go to the Start menu ("IC") and then the WhatsApp menu to send a message to a contact named "Francisco", with containing the text "*hola*" in Spanish ("*hello*" in English). The contact's name and the word "hola" were suggested by the system when one letter had been selected. A minimum of eight actions were needed to complete this task ("IC", "Send WA", "F", "Francisco", "H", "hola", "OK", "Confirm").
8. Access the Start menu ("IC"), then the Music menu ("Music") to turn off Spotify and return to NC ("Stop").
9. Turn down the light to a low intensity ("Low light") and set the color to blue ("Blue light"), and then go to the NC menu ("No control").

10. Access the Start menu (“IC”) and then the TV menu (“TV”) to turn on the TV (“ON/OFF”), set it to channel 7 (“Channel”, “7”, “Validate”), turn up the volume (“Vol+”), set a two-minute timer (“Timer”, “2”, “Validate”) and stay in the NC menu until the TV is turned off (“NC”).
11. Go to the Start menu (“IC”) and turn off the lamp (“Light off”).
12. Turn off the air conditioning (“Air OFF”).
13. Access the Announcement menu (“Announcement”) and enter the word “*fin*” (“F”, “fin”, “OK”, “Confirm”) (in English, “*end*”), to communicate that the experiment had finished.

After performing all the tasks required in the online phase, the EEG equipment was dismantled so that the participant could comfortably answer a set of questionnaires as discussed in Section 2.6.2. In the case of the patients, the experimenter asked them the questions orally and they responded via their usual method of communication with the people around them (e.g., by hand gestures or winks). Once the questionnaires were complete, the experiment was concluded for the participant.

2.6. Evaluation

We used two types of metrics to evaluate the control of the system. Performance measures were applied to quantify the objective accomplishment of the tasks carried out by the user, while questionnaires were used to describe the user's subjective experience of controlling the system.

2.6.1. Performance

We assessed the performance of the system in both the calibration phase and the online phase. The performance in the calibration phase was used to adapt the number of sequences based on the criteria set out in Section 2.5. However, it should be noted that there was no feedback from the calibration phase, since the classifier parameters had not yet been calculated. The performance in the online phase allowed us to evaluate the actual control of the system. The variables used to measure performance in the calibration phase were accuracy and WSR, while for the online task we used measures such as the time spent performing the task, the accuracy and success in the standby state (staying in the NC menu while listening to the radio or watching TV). For the online task, in addition to the errors that could have arisen in the system when the user selected the desired command using UMA-BCI Speller, errors could also have occurred when executing the commands sent from UMA-BCI Speller to Google Assistant and the subsequent devices and applications (e.g., failure to understand a voice command, or failure of the infrared device or smart plug).

2.6.2. Questionnaires

In order to assess the subjective user experience, three questionnaires were used: (i) SUS [36], (ii) raw NASA-TLX [37] and (iii) an ad hoc questionnaire designed by the researchers to extract additional information. All questionnaires were presented in Spanish, the native language of the participants.

a. The SUS was used to perform a general evaluation of the usability of the BCI system employed. It consisted of 10 items to be evaluated according to a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The overall usability score provided by this questionnaire ranges from 0 to 100 (see [36] for the details of scoring the SUS). According to [38] a score of 70 is suggested as the acceptable minimum. The items used in the present work were the following (the name of the variable has been added at the end of each item in parentheses):

1. *I believe that patients and caregivers could use this application frequently.* (frequency of use).
2. *I found this application unnecessarily complex.* (complexity).
3. *I thought the app was easy to use.* (ease of use).
4. *I think I would need help from a tech skilled person to use this application.* (need for technical support).
5. *I found the various functions in this system were well integrated.* (integration of functions).
6. *I think the application is very inconsistent when executing the various actions.* (inconsistency).
7. *I would imagine that most people would learn to use this system very quickly.* (ease of learning).
8. *I found the application very cumbersome to use.* (cumbersome use).
9. *I felt confident using this application.* (user confidence).
10. *I needed to learn many things before I was able to use this application.* (need for knowledge).

b. The Raw NASA-TLX measures the user workload produced by the control of the system. This questionnaire is a modification of the NASA-TLX [39]. This modification has been widely used and consists of shortening the test to reduce the time required [37]. The Raw NASA-TLX is a multidimensional questionnaire with six subscales that are scored from 0 to 100 (mental demand, physical demand, temporal demand, performance, effort and frustration), in intervals of five units. Higher scores will mean higher workload. The endpoints for each subscale are “*very low/very high*” except for the performance subscale, which has “*perfect/failure*” endpoints. The total workload was calculated by averaging the scores obtained in each of the subscales. The items used were the following (the name of the variable has been added at the end of each item in parentheses):

1. *How mentally demanding was the task?* (mental demand)
2. *How physically demanding was the task?* (physical demand)
3. *How hurried or rushed was the pace of the task?* (temporal demand)
4. *How successful were you in accomplishing what you were asked to do?* (performance)
5. *How hard did you have to work to accomplish your level of performance?* (effort)
6. *How insecure, discouraged, irritated, stressed and annoyed were you?* (frustration)

c. In addition to SUS and raw NASA-TLX, a small ad hoc questionnaire was prepared to evaluate additional aspects that were considered relevant. The answers to this questionnaire could contain useful information that could be considered in future proposals or modifications of the presented system. The questionnaire consisted of five open-response items. It was not filled in by the patients, since at this point, the experiment with them had already lasted more than two hours, and they felt overtired after their efforts during this period. The time required to complete this questionnaire by the patients would also have been longer than normal, due to their difficulty in answering it. The following items were used (where the name of the variable is added at the end of each item in parentheses):

1. *List up to three negative features of the interface.* (negative features)
2. *List up to three positive features of the interface.* (positive features)
3. *Would you add any functionality to any of the controlled applications or devices? If so, which one(s)?* (additional functionalities)
4. *Would you add control of any other application or device? If so, which one(s)?* (additional controlled applications or devices)
5. *Additional comments.* (additional comments)

3. Results

In this section, we present the results for the performance metrics (relative to the calibration and online phases) and the findings from the subjective questionnaires for both the healthy participants and the ALS patients.

3.1. Calibration phase

Fig. 4 illustrates the average accuracy obtained by healthy participants during the calibration phase. Most of the participants (10 out of 12) achieved 100 % accuracy with only three sequences. When the maximum allowed number of sequences was used (i.e., five sequences), all participants achieved 100 % accuracy. Since all participants obtained their highest WSR on or before the third sequence, as per the selection criteria explained in Section 2.5, three sequences were used for all of the healthy participants in the online phase. The good results obtained for the performance were consistent with those shown in Fig. 5 for the grand average ERP waveform, where the signals associated with the target and non-target stimuli can be clearly distinguished, especially for the P300 component (with a peak around 490 ms for the target stimulus on almost every channel).

It is worth remembering that the accuracy results in the calibration phase have been obtained without using a cross validation method, so they are not suitable for comparison purposes. All the calibration data was used to train the classifier for the online phase, and the obtained accuracy and WSR to select the specific number of sequences to be applied online. Furthermore, the short calibration phase was performed using only one of the system interfaces (the spelling menu), while in the online phase several menus changed depending on the user selections. These two reasons explain the differences that the reader will find below between the calibration and online accuracies.

The patients achieved lower performance than the healthy participants, since it was not until sequence 7 that they all reached 100 % accuracy (Fig. 6). Furthermore, it can be seen that the obtained ERP waveforms were not particularly similar between patients (Fig. 7). For example, a possible P300 with a peak around 500–600 ms can be observed for P02, while for P03, there is a negative peak around 200–300 ms. Nevertheless, the classifier performed adequately, even for P01, whose ERP waveform seemed to show lower differences between the target and non-target stim-

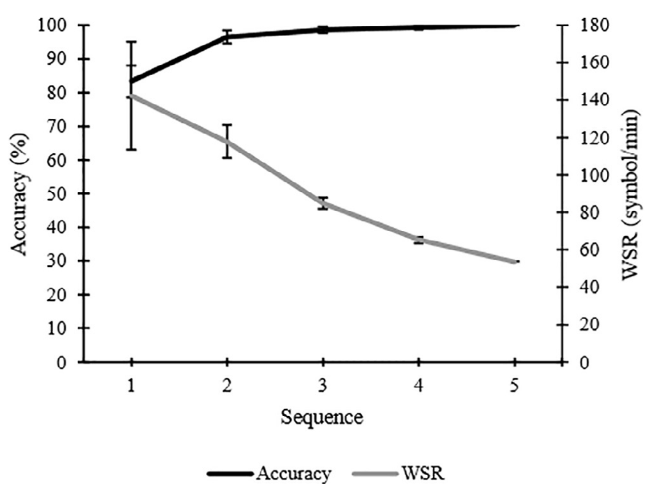

Fig. 4. Average (±standard error) accuracy (%) and written symbol rate (WSR, symbols/min) obtained by the healthy participants in each of the sequences in the calibration phase.

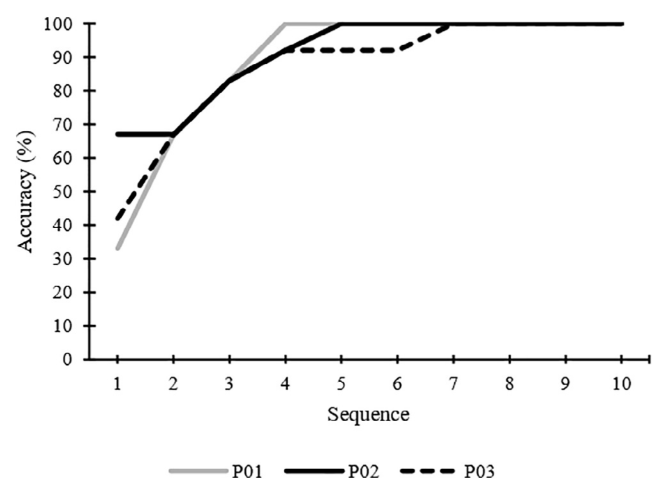

Fig. 6. Accuracy (%) obtained by each ALS patient in each of the sequences in the calibration phase.

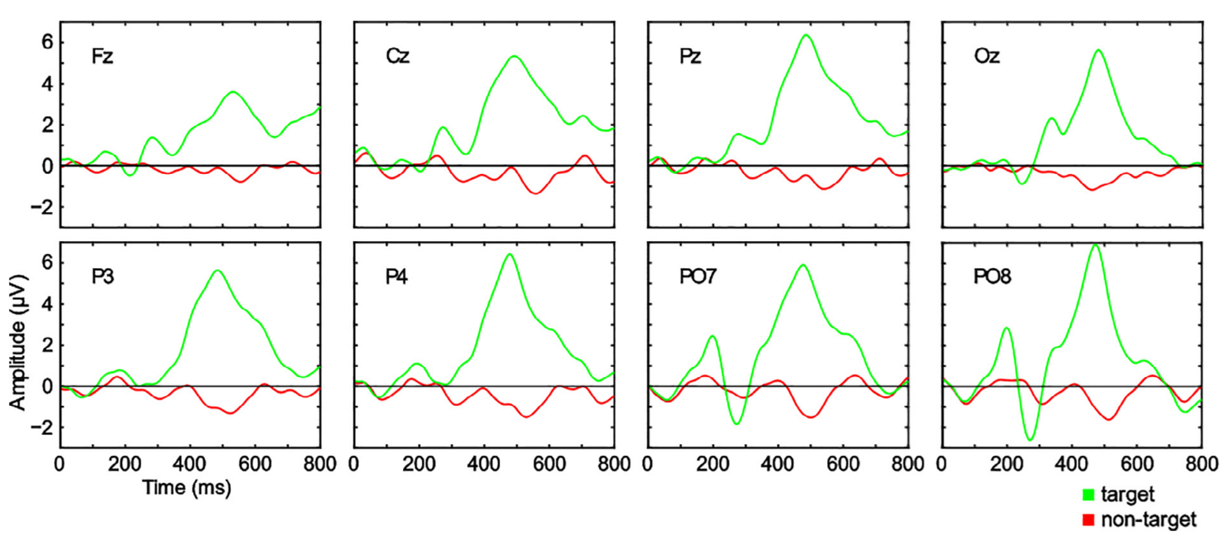

Fig. 5. Grand average event-related potential waveforms (μV) for target and non-target stimuli in each electrode position, for healthy participants.

uli than for the other participants. Based on the criteria explained in Section 2.5, the number of sequences used for the patients in the online phase were as follows: P01, seven sequences; P02, six sequences; and P03, seven sequences.

3.2. Online phase

All of the healthy participants completed the test except H05, who abandoned the experiment due to the large number of errors that were occurring (when she stopped, she had an accuracy of 41.77 % and was on task 5, which involved managing Spotify). This participant was therefore excluded from the averages reported in this section. The average accuracy obtained by the healthy participants who finished the test was 80.68 ± 11.91 % (Table 3). Only two participants (H03 and H06) achieved an accuracy of below 70 % (a threshold widely accepted in the BCI community and proposed in [40]) during the course of this task. The average number of total incorrect selections was 17.18 ± 13.78 (out of 78.09 ± 20.67), which included 9.82 ± 7.56 selections of dummy elements with no consequences. The average time required to complete all the tasks was 29.27 ± 7.2 min, including periods of optional rest in the NC menu. Specifically, the participants remained in the NC menu for a total time of 2.74 ± 1.07 min (corresponding to an average of 7.91 ± 3.14 random selections of dummy commands). If these standby periods are subtracted, we see that it took users an average of 26.53 ± 7.02 min to complete the required tasks. For the two tasks that involved staying in the NC menu in the standby state (while listening to the radio or watching TV), only three participants did not complete the required time. Specifically, for the task of waiting at least one minute in the NC menu while listening to the radio, *H*01 and *H*11 did not complete the required time (that is, they abandoned the NC menu before one minute had

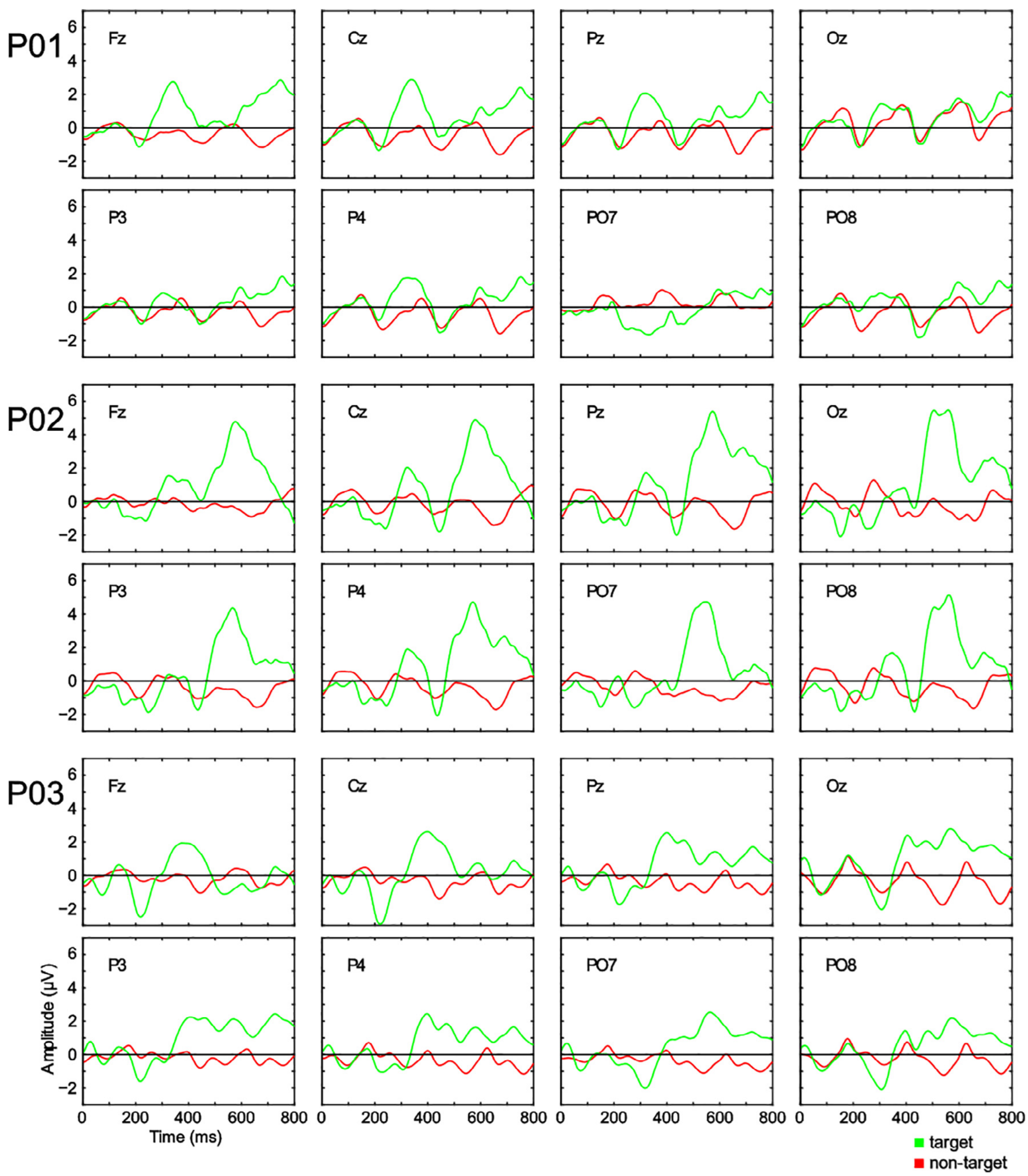

Fig. 7. Grand average event-related potential waveforms (μV) for target and non-target stimuli in each electrode position, for patients.

Table 3
Results of the online task in terms of the time needed to complete the tasks (Total time, min) and the overall accuracy (Accuracy, %).

User	Total time (min)	Accuracy (%)
H01	26.55	84.06
H02	22.81	94.83
H03	41.16	64.35
H04	24.51	90.48
H06	42.86	66.37
H07	22.81	94.92
H08	32.66	71.26
H09	21.79	96.49
H10	31.64	72.62
H11	27.91	100
H12	27.23	79.17
Mean of healthy users	29.67 ± 7.2	80.68 ± 11.91
P01	40.66	78.87 %
P02	34.31	73.85 %
P03	39.56	60.56 %

passed). In regard to the task of watching TV for two minutes, neither H03 nor *H*11 accomplished this. *H*11 admitted that he forgot about both waiting tasks and did not even try; he did not select a dummy command in either case from the NC menu.

The number of sequences chosen for the patients was higher than for the healthy patients; P01 and P03 used seven sequences, while P02 used six. The accuracy obtained by each participant was as follows: P01, 78.87 %; P02, 73.85 %; and P03, 60.56 %. It can be observed that all the accuracy values were below the average for the healthy participants (80.68 ± 11.91 %), even though the number of sequences used was higher. Hence, it is not surprising that the total time taken to complete the task was also higher than the average for the healthy subjects (P01, 40.66 min; P02, 34.31 min; P03, 39.56 min; average for healthy users, 29.67 min). To ensure that the protocol was completed, the experimenters were more flexible with the patients, as they did not want them to become over-fatigued due to a session that was too long, and there were several particularities that should be mentioned. The tasks involving air conditioning were omitted for all three patients, as this device was not available in their homes. In addition, as explained below, both P02 and P03 experienced some inconvenience when executing the procedure. Firstly, P02 forgot to turn on the light at the beginning of the experiment, and the researchers felt it was important not to interrupt the patient's execution and to continue the experiment. Secondly, P03 had four consecutive failures in the task of selecting the desired musical style, so the experimenters considered the accidental selection of an incorrect musical style as valid (although this selection was noted as an error). In addition, since this participant's (P03) session was taking too long, the TV control task was simplified on the fly, and he was only asked to (i) turn on the TV, (ii) turn up the volume and (iii) set a timer for two minutes. However, he made a mistake and turned off the TV instead of setting the timer, after which the session was terminated without the participant completing the task of announcing the end of the session. For the task of staying in NC listening to the radio, P03 was the only one to complete this, while for the TV this task was completed by P01 and P02 (as mentioned above, this task was omitted for P03 due to the long duration of the experimental session).

The errors made by Google Assistant when interpreting voice commands (regardless of whether the commands were selected correctly or incorrectly by the user) are summarized below. One error arose when H06 selected the "Release" item by mistake from the Spotify menu, and the command was not executed due to a global problem in the app (https://twitter.com/SpotifyStatus/status/1402216192794890249). The second error arose when H08 selected the "Track +" command from Spotify menu, which was not executed. This was due to Google Assistant failing to understand the requested command, as it replied the following, "*¿Me puedes repetir qué quieres decir?*" ("*Can you repeat what you want to say?*" in Spanish). Finally, when *H*10 selected the command "Air ON", this was not executed. Since Google Assistant did not respond to this task, it is possible that this last failure arose in the infrared device, which may not have successfully sent the signal to the air conditioner.

3.3. Questionnaires

3.3.1. System usability scale

Regarding the subdimensions assessed with the SUS by the 11 healthy participants who completed the online phase, all the positive items (odd items: frequency of use, ease of use, integration of functions, ease of learning and user confidence) were scored with an average of above four points, while the negative items (even items: complexity, need for technical support, inconsistency, cumbersome use and need for knowledge) obtained average values equal to or below two points (Fig. 8). The average score for the overall usability was 88.18 ± 7.67. No healthy participant achieved a score of below 70 points (the lowest was 77.5 for *H*10). It can therefore be concluded that the system was given a highly positive rating by the healthy users. For the patients, there was a higher disparity in the results (Fig. 9). Both P01 and P02 saw the system in a generally favourable light, since almost all of the positive subdimensions were scored at the maximum (five points). The exception was the confidence score of four given by P01. None of the negative items scored above three points. However, P03 was less pleased with the system and only scored two positive subdimensions higher than three (four points for integration of functions and ease of learning) and gave a score of three for complexity, need for technical support and inconsistency. This finding was supported by the results for the overall usability variable, as P01 and P02 achieved higher scores (82.5 and 97.5 points, respectively) than P03 (60 points), who achieved the lowest accuracy in the online phase (60.56 %).

3.3.2. Raw NASA-TLX

The average scores given by the 11 healthy participants for each of the subdimensions of the raw NASA-TLX questionnaire can be seen in Fig. 10. As expected, due to the number of devices to be controlled and the nature of the task, the subdimensions with the greatest weights for the total workload were temporal demand (32.73 ± 19.92) and mental demand (30.91 ± 24.58), as opposed to,

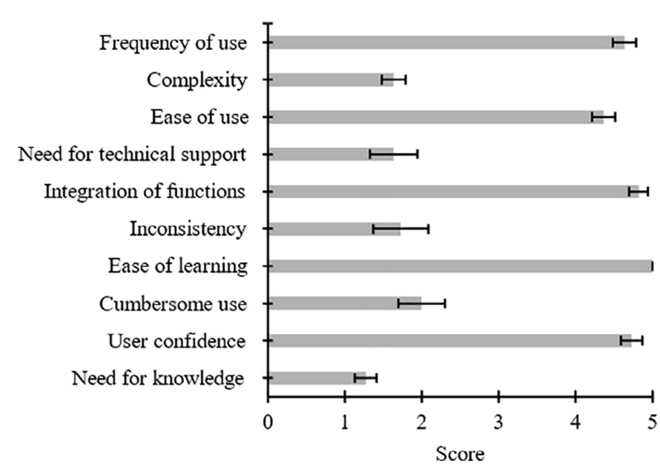

Fig. 8. Average scores (±standard error) allocated by healthy participants for each of the subdimensions of the System Usability Scale.

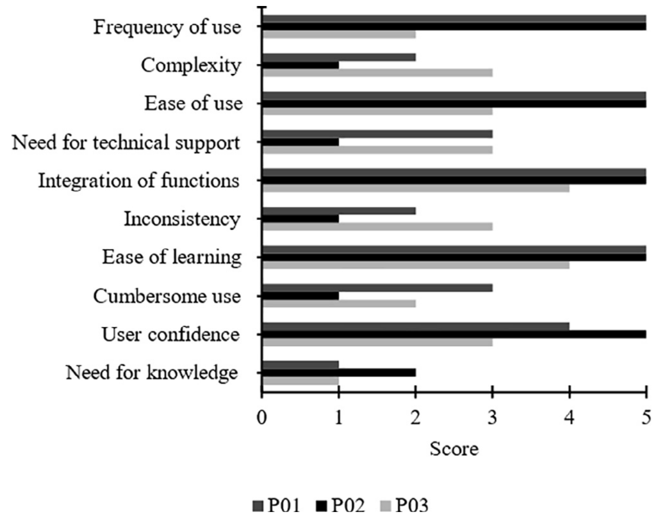

Fig. 9. Scores allocated by each ALS patient for each of the subdimensions of the System Usability Scale.

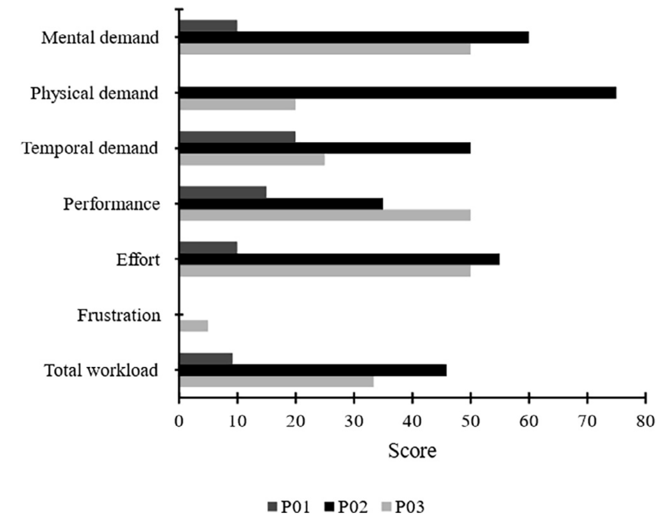

Fig. 11. Scores allocated by ALS patients to each of the subdimensions of the raw NASA-TLX questionnaire.

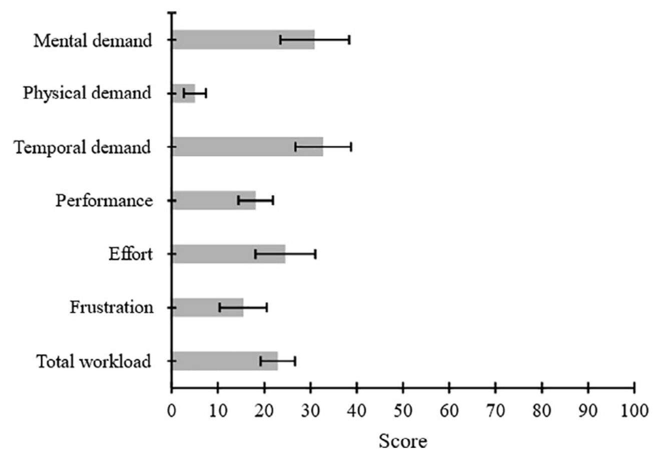

Fig. 10. Average results (±standard error) reported by healthy participants for each of the subdimensions of the raw NASA-TLX questionnaire.

for example, physical demand (5 ± 8.06). The average total workload reported by healthy participants was 22.92 ± 12.37. For the patients, there was significant heterogeneity in the scores for the NASA-TLX items (Fig. 11), as for the SUS-related variables. In general, while the scores allocated to the subdimensions by P01 were relatively low (with none above 20 points), the scores given by P02 and P03 were considerably higher. This finding is corroborated by the results for the total workload variable, which were as follows: P01, 9.17 points; P02, 45.83 points; and P03, 33.33 points.

3.3.3. Ad hoc

The answers given by 10 of the healthy participants to each item are described below (one participant did not answer this questionnaire). Only the answers that were considered important by the researchers are reported here.

1. Negative features. Three participants agreed that the system was slow in terms of constructing the voice commands (*H*01, *H*11 and H12). Two participants stated that the stimuli were presented too quickly (H02 and H07). Only one participant mentioned the inconvenience of the cap and the use of the electrolyte gel (H03). Two participants highlighted the need to concentrate in order to control the system (*H*01 and *H*11). Two participants criticized the occurrence of errors during the control tasks (H06 and H12). One participant also found that the descriptions of some commands were confusing (H08), while another stated that the selection of options allowed by the system could be improved (H09). Finally, one participant felt that the way the items were distributed in the interface could be improved (*H*10).
2. Positive features. The positive characteristic for which most agreement was found was the ease of use of the system (*H*01, H02, *H*11 and H12). Three participants felt it was simple (*H*01, H02 and H12), and two found it useful (*H*01 and H06). In addition, some participants reported that the interface was effective (H03), agile (H09), comfortable to use (*H*11), highly customizable (H12), that it simplified the use of devices in the environment (H06), that it provided autonomy (H07), and that the use of icons and images was helpful (H09 and *H*10).
3. Additional functionalities. Two participants stated that it would be interesting to add a specific submenu for air conditioning with more options (*H*01 and H09), and to move the existing light options to another submenu to make the start menu cleaner (*H*01). Another participant felt that it would be useful to be able to change the radio station (H07). Finally, two participants reported that it would be nice to be able to add more music genres or to choose a playlist from their own Spotify account (H06 and H02).
4. Additional controlled applications or devices. The applications or devices suggested by the healthy participants were alarms or reminders (*H*01), blinds (H02 and H08), a robot vacuum cleaner (H02), an audiobook or e-book (H07), online searches (H07), a computer (H07), a coffee maker (H09), Chromecast, for controlling a smart TV with Netflix, Amazon Prime video, etc. (*H*10), doors and windows (*H*11) and social networks (H12).
5. Additional comments. Only three participants provided additional comments. One emphasized that he found the experience of controlling the proposed system very interesting and interactive (H02). In a similar vein, another participant indicated that the experiment had been enjoyable and entertaining (H08). Finally, another participant concluded that although there are faster technologies than BCIs, they do not have the potential of this one (H12).

4. Discussion

In our experiments, several devices and applications were shown to be successfully controlled. This section has two main objectives: (i) to discuss and deepen the results obtained from both healthy users and patients; and, where possible, (ii) to contextualize them with previous literature on performance metrics and subjective questionnaires. It is worth noting that these comparisons between studies should be made with caution, as the differences between them are often significant (e.g., the EEG instrumentation used, the specific BCI paradigm, or the experimental procedure) and the required statistical analyses have not been carried out.

4.1. Performance

The average performance achieved by the healthy users during the online session was 80.68 %, clearly above the 70 % threshold established in [40] for efficient communication. Only three healthy participants (of 12) fell below this threshold (H03, H06 and H05, whose results were not included in the average calculation). Two of the three patients exceeded this threshold (P03 did not). It should be emphasized that the participants only underwent a short calibration process, and that most had no previous experience in handling these systems (only H08–*H*10, P01 and P03 had previous experience). It should also be remembered that the goal was not to achieve the highest possible accuracy, since the number of sequences used was adapted to maximize efficiency in terms of the selection of commands through the WSR.

The accuracy achieved by the patients (P01, 78.87 %; P02, 73.85 %; P03, 60.56 %) was lower than for the healthy participants (80.68 %). However, previous reports in the literature have not clearly established a relationship between performance and a diagnosis of ALS (e.g., [41]). In the present work, it would therefore be risky to assume that the lower performance of the patients compared to the healthy participants was due to their condition. In this case, the differences between the healthy participants and patients may be due to chance (as only three patients took part), the testing environment (the laboratory versus the patient's house), or other factors that need to be studied separately (e.g., age or degree of general familiarity with the technology).

A comparison with our previous study that followed a similar procedure (i.e., the use of voice commands built using a BCI system for interpretation by a voice assistant to control diverse messaging systems [27]) shows that the accuracy obtained here was slightly lower (80.68 % vs 86.14 %), but the information transfer rate (ITR) was higher (25.9 bits/min vs 21.69bits/min). The ITR is the number of bits transmitted per second and provides a more general evaluation than accuracy since, besides considering it, it takes into account the number of elements available in the interface as well as the time needed for each selection, which depends on the number of sequences used [42]. It is difficult to establish a reliable comparison between different experiments as well as to explain why the accuracy was better in the first experiment and the ITR in the second. Besides the possibility that the differences are due to chance, the studies differed in some aspects such as the type of stimulation used to elicit ERPs (white flash for the first study and images for the current one) or the tasks to be performed. However, it is admitted that the better results in at least the ITR were expected since previous studies indicated that the use of images as stimulus to be attended improved the performance of an ERP-based BCI under the RCP [43], which in the present experiment translated into a lower use of sequences for the online task compared to the previous experiment that used the color change to white (in the present experiment all participants used 3 sequences, which was the lowest number possible, while in the previous experiment the average was 4.25).

It is worth mentioning that the system has not been optimized to improve accuracy since a classic RCP and a classifier based on a simple SWLDA have been used. The aim was to use only the standard options of the used BCI software (UMA-BCI Speller and, therefore, BCI2000), as would be done by a user without extensive technical knowledge. Once the home automation system proposal has been validated under these conditions, new changes can be added to improve performance, such as adding an artifact removal/correction method, modifying the number of stimuli or the way they are presented (e.g., using the checkerboard paradigm [35]) or applying alternative techniques to improve the classifier accuracy [44] or reducing the calibration time [45]. It is also important to consider a BCI design focused on the user's capabilities, with the option of employing other sensory modalities in addition to visual, such as auditory or even tactile (e.g., [46,47]).

The control system itself gave rise to several errors that were not caused by incorrect execution by the users but by failures within the system itself (e.g., of Google Assistant or the devices to be controlled). These types of errors were also identified in our previous publication [27]. However, in the present work, this kind of error only occurred three times: one that was due to a problem with the application used (Spotify), another that was due to a failure by Google Assistant to understand the voice command, and another that was due to failure of the infrared device. Based on our previous work in [27], it was possible to identify which voice commands were more likely to be misunderstood by Google Assistant. This highlights the importance of describing these types of errors in detail, so that they can be considered in future work to improve the system. One way to avoid this possible error in the recognition of voice commands would be to test them extensively prior to the implementation in the BCI system in order to detect the potential errors and to modify the spelling of the command sentence. In this experiment, for example, an error occurred regarding the "Track +" command (it only happened once), designed to make the music application switch to the next song. The sentence that the BCI interface sent to the voice assistant was "Ok Google, next song"; perhaps a better specification of the command context might be the solution, for example with "Ok Google, play the next song on Spotify".

Regarding the timing of the interaction with the domotic system, two aspects should be mentioned. On the one hand, the time involved to perform a trial does not differ from other visual ERP-based BCI systems: in the case of healthy patients, which all used three sequences of stimuli presentations, the delay to select an item was 9.41 s (the RCP consisted of a 7 $\times$ 7 matrix with a SOA of 224 ms). On the other hand, we should consider the delay added by the voice-operated virtual assistant: although it is a variable time depending on external factors (such us the state of the smartphone running the assistant or the load of the data network), it used to be less than 10 s. As an example, to the command "Ok Google [one second pause], play music in Spotify", the system took nine seconds to respond (including the time used to put into voice the sentence) in average conditions.

4.2. Questionnaires

Of the papers discussed in the introduction (Table 1), only [18], [17] and [23] employed subjective measures to evaluate the application. However, of these three studies, only [23] used a standardized questionnaire (NASA-TLX) that would allow us to contextualize our current work, since only ad hoc items were used in [18] and [17]. It is also worth considering our previous work in [27], since it used voice control and employed the same questionnaires as in the present study, which greatly facilitates a comparison and contextualization of these works. Hence, as far as possible, the results obtained here will be contextualized with those obtained in the aforementioned studies.

4.2.1. System usability scale

The SUS scores reported for the application were highly positive. A score of 88.18 ± 7.67 points was obtained on the overall usability measure, where 70 is the threshold for a good level of usability according to [38]. None of the healthy participants had a score below this threshold. The average scores for the healthy participants and those recorded for each subdimension were also reasonably high: all negative subdimensions were scored between 1.27 and 2 points, and the positive subdimensions were scored between 4.36 and 4.82 points. The scores from the patients were more varied: these were high for P01 and P02 (82.5 and 97.5 points, respectively) but were below the mentioned threshold for P03 (60 points), which was as expected considering the low online performance of his session. These results can only be contextualized against those obtained in our previous work, which included only healthy participants [27]. The usability score was slightly more positive in the current work since the overall usability in our previous work was 82.5 ± 15.63 points. It therefore seems that users rated this application, which was related to home automation control, as more usable compared to one that focused on sending text messages. It is also notable that in this work, we were able to use what was learned and what was suggested by the participants in our previous study to improve the system (e.g., adding options proposed by the participants themselves, the use of images for stimulation rather than highlighting letters, and the use of voice commands that were easily interpreted by Google Assistant).

4.2.2. Raw NASA-TLX

In the present study, the raw NASA-TLX questionnaire yielded a positive assessment of the application. The average total workload score given by healthy participants was 22.92 ± 12.37 points, which can be considered reasonably low. In addition, the scores for the different subdimensions were averaged at between five and 30.91 points. The patients in the present study gave varied scores for the total workload (9.17, 45.83 and 33.33 points for P01, P02 and P03, respectively). As can be observed, these scores are quite heterogeneous, and it would be interesting to explore the reasons for this. For example, the difference in the scores given by patients may be due to multiple factors such as susceptibility to tiredness, fatigue, the effort required to perform the test, frustration tolerance or physical condition. The results of this work can be compared those of [23] and [27]. The study in [23] used SSVEP and electromyography (EMG) signals for the control of a wheelchair, a nursing bed, a TV, a telephone, curtains and lights, and included healthy participants and patients, but only reported the subdimensions of the questionnaire (rather than the total workload). A comparison of the present work with our previous work in [27] indicates that lower average scores were obtained for each subdimension in the present study, both for healthy participants (5 to 33 points in the present work; 21 to 78 points in [27]) and for patients (one to 40 points in our work; 25 to 55 points in [27]). However, problems arising from the use of averages for the patients should be emphasized, since the patient sample size was low for both works (three in the present work, and five in [27]). The scores in [27] were also higher than those reported here, for all subdimensions. This fact is reflected by the total workload measure reported by healthy participants (as the study did not include patients) of 31.55 ± 17.44 points, whereas in the present work it was 22.92 ± 12.37 points.

4.2.3. Ad hoc

Thanks to the ad hoc questionnaire, several interesting points were extracted that should be considered in future applications or modifications to this application. It is important to note that the system was considered both useful and easy to use by several participants. However, some users found it to be slow, and reported that the use of gels was annoying. The speed of the system could be improved by allowing an acceptable accuracy based on a smaller number of sequences, or by reducing the number of elements available in the interfaces, which could be easily achieved using UMA-BCI Speller. The problem with the use of gel could be addressed through the use of semidry electrodes, for example, as these do not require gel, offer increasingly better results and may be more suitable for daily use of the system [48]. Regarding the other applications and devices suggested by the participants, most of the suggestions could be implemented with relative ease via the interface (e.g., setting an alarm or controlling a smart TV). As mentioned above, the use of Google Assistant to control devices and applications via voice commands is widespread, and it would be simple to add the desired commands to UMA-BCI Speller (e.g., setting an alarm or reminders through Google Assistant, or controlling a robot vacuum cleaner or a smart TV with Netflix or Amazon Prime video).

In summary, the set of subjective questionnaires yielded useful data, allowing us to determine that the proposed system was simple to operate and provided a pleasant experience for most of the participants. The data gathered in this study could also be used to develop the system further.

5. Conclusions

In this paper, we have successfully demonstrated the use of a BCI system for home automation control that is flexible and can potentially be adapted to the needs of a user. The results from the performance and subjective questionnaires confirm that the system could be both useful and suitable for patients. To our knowledge, this is the first proposal of a domotic setup based on the creation of specific commands via an ERP-based BCI system in which these commands are converted into voice commands to be sent to a virtual assistant on a smartphone. In general, BCI systems are difficult to adapt to allow for control of external devices and applications. However, voice control is becoming increasingly common, and the idea underlying this proposal is to facilitate the control of devices already adapted to voice commands, something that can be essential for the target population of these interfaces. It is important to remember that the users of these systems (i.e., patients or their caregivers) may not have the technical expertise necessary to manipulate complex systems. UMA-BCI Speller software once again proved to be a useful tool that is highly adaptable in terms of controlling numerous devices in the environment by bypassing voice commands. However, despite this ease of use, it is necessary that the person who configures the system understands its operation independently of the BCI system. For example, if the user wants the BCI system to control the television through the infrared controller, the user must learn how to operate the infrared controller. Nevertheless, all the applications and devices used in this work are aimed at the general public, so the technical requirements for their control should not be considered high. It should also be noted that, in comparison to the works presented in Table 1, our proposal is the only one that allows a free and customized construction of the commands, either through the use of the Spelling menu or the accessible manipulation of the UMA-BCI Speller tool. Therefore, the novelty of the present work lies in the implementation of a BCI system with different menus, fully customizable, that allow the construction of voice commands focused on the control of applications and external devices.

In future work, it would be advisable to explore the long-term daily use of these systems by patients. This would make it possible to test the system in the real world and to continue improving it. It would also be advisable to evaluate not only the software but also the hardware, with the aim of developing low-cost, portable devices that do not require technical knowledge or specialized technicians for their use.

CRediT authorship contribution statement

Francisco Velasco-Álvarez: Conceptualization, Methodology, Software, Writing – review & editing, Investigation. **Álvaro Fernández-Rodríguez:** Methodology, Writing – original draft, Formal analysis, Investigation. **Ricardo Ron-Angevin:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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