Biocybernetics and Biomedical Engineering 45 (2025) 528–538

Contents lists available at ScienceDirect

Biocybernetics and Biomedical Engineering

journal homepage: www.elsevier.com/locate/bbe

Research Paper

Toward the integration of mixed reality and brain-computer interfaces based on code-modulated visual evoked potentials

Selene Moreno-Calderón [a,*], Víctor Martínez-Cagigal [a,b], Ana Martín-Fernández [a], Eduardo Santamaría-Vázquez [a,b], Roberto Hornero [a,b]

[a] Biomedical Engineering Group, University of Valladolid, ETSIT, Paseo de Belen 15, 47011, Valladolid, Spain
[b] Centro de Investigación Biomédica en Red de Bioingeniera, Nanomedicina (CIBER-BBN), Valladolid, Spain

ARTICLE INFO

Keywords:
Brain-computer interface (BCI)
Code-modulated visual evoked potential (c-VEP)
Mixed reality (MR)
Eyestrain
Electroencephalography (EEG)

ABSTRACT

Background and objective: Brain-computer interface (BCI) systems can assist individuals with severe motor disabilities by enabling communication through their brain signals using spellers, which allow selecting commands from a set of options. For this technology, accuracy, speed and user comfort are essential. Code-modulated visual evoked potentials (c-VEPs) have demonstrated promising performance in BCI control. Integrating BCI systems with mixed reality (MR) could provide portability and autonomy. However, to the best of our knowledge, no existing studies have explored the feasibility of combining MR with c-VEP-based BCIs. This study aims to: (1) evaluate the performance of integrating MR with c-VEP-based BCIs and (2) study the visual fatigue induced by c-VEPs compared to traditional screen. *Methods*: Twenty participants used a 36-character speller to select words in both MR and traditional screen conditions. Metrics like accuracy and information transfer rate (ITR) were measured. Usability and eyestrain were evaluated through questionnaires. *Results*: The integration of MR with c-VEPs achieved an accuracy of 96.71 % and an ITR of 27.55 bits/min, compared to 95.98 % accuracy and 27.10 bits/min for the conventional screen condition. The questionnaires revealed minimal levels of visual fatigue in both conditions and high usability. No significant differences were observed between conditions in terms of performance or visual fatigue. *Conclusions*: The c-VEP-based speller with MR-BCI technology proved feasible, achieving performance levels similar to the conventional setup, with high accuracy in both conditions. The study also found comparable visual fatigue between MR and traditional screens, supporting the practicality of MR integration in BCI systems.

1. Introduction

A brain-computer interface (BCI) is defined as a communication system that enables users to interact with their environment without the use of muscles or peripheral nerves [1]. Specifically, BCI systems achieve this by decoding user intentions through the monitoring and processing of brain activity. The most commonly employed technique is electroencephalography (EEG), which is non-invasive, portable and cost-effective compared to other methods. Traditionally, these systems have been used as an alternative means of communication for individuals with motor disabilities, allowing users to achieve greater independence and regain a significant degree of social interaction [1].

Although BCI systems can be employed for a wide range of assistive applications, such as wheelchair control [2], web navigation [3], video gaming [4] or the operation of everyday electronic devices [5], the most common application for augmentative and alternative communication is the BCI speller [6]. This application is particularly useful as it enables users to write, through a graphical user interface that displays letters, numbers and special characters. The first speller application was introduced by Farwell and Donchin in 1988 [7]. Different control signals, such as P300 potentials and steady-state visual evoked potentials (SSVEPs), have been employed to develop BCI spellers, achieving varying performance in terms of accuracy and information transfer rate (ITR) [6]. For BCI spelling applications, speed, accuracy and user comfort are the most important factors.

Nevertheless, recent advancements have introduced code-modulated visual evoked potentials (c-VEPs), as a novel control signal, demonstrating superior accuracy and selection speeds [8,9]. This control signal encodes commands by using shifted versions of a pseudo-random sequence. Usually, visual stimuli are displayed to the user as a series of

* Corresponding author.
E-mail addresses: selene.moreno@uva.es (S. Moreno-Calderón), victor.martinez.cagigal@uva.es (V. Martínez-Cagigal), ana.martin.fernandez23@uva.es (A. Martín-Fernández), eduardo.santamaria.vazquez@uva.es (E. Santamaría-Vázquez), roberto.hornero@uva.es (R. Hornero).

https://doi.org/10.1016/j.bbe.2025.06.003
Received 26 January 2025; Received in revised form 25 June 2025; Accepted 29 June 2025
Available online 28 July 2025

black and white flashes, which blink in accordance with the sequence. The application of c-VEPs in communication and control systems holds significant promise, owing to their capability to achieve high accuracy with reduced calibration times (e.g., > 90 % with selections of 0.5-5s per command and calibrations of 1–5 min) [9]. Several spellers have been developed using c-VEPs. In 2019, Nagel et al. [10] introduced a keyboard including letters, numbers and special characters, obtaining an accuracy of 98.2 % and an ITR of 109.1 bits/min in 10 users. In addition, Gembler et al. [11] developed a speller with a suggestion dictionary, displaying 18 commands on the screen: 4 upper commands with grouped letters and 4 lower commands with suggested words and a correction command. This system, tested with 18 users, achieved an accuracy of 95.9 % and an ITR of 57.8 bits/min. In 2021, Verbaarschot et al. [12] presented a c-VEP keyboard for patients with amyotrophic lateral sclerosis (ALS). The study involved three groups: 12 healthy subjects under 35 years, 8 healthy subjects over 35 years and 10 ALS patients. The accuracies and ITRs for a task involving 22 selections were 94.3 % and 24.8 bits/min, 88.3 % and 21.0 bits/min and 79.3 % and 20.3 bits/min, respectively, for each group. Spellers have been utilized for an extended period, not only for augmentative and alternative communication (AAC) but also to evaluate the performance of BCI systems.

The rise of extended reality (XR) technologies has further expanded the potential of BCI systems. XR encompasses immersive technologies like virtual reality (VR), augmented reality (AR) and mixed reality (MR) [13]. Its capacity to create highly immersive, interactive environments is critical for driving successful outcomes. As this field has rapidly evolved and gained traction, its relevance across sectors has only increased [14]. XR and head-mounted displays (HMDs) are optimal candidates for generating visual stimuli, as the images are projected directly into the user's eyes, enhancing contrast, reducing the distance between the user and the stimuli and simultaneously minimizing noise factors from the surrounding environment [15]. Within this context, MR refers to environments where real and virtual subjects and objects interact in real time, allowing users to engage with both types of components, i.e, users can naturally interact with virtual elements within the physical space [16]. Combining the strengths of AR and VR, MR offers versatile applications. For instance, He et al. [17] investigated how stimulus color affects SSVEP-based BCI performance in MR environments, demonstrating that color and background influence system performance. Similarly, Li et al. [18] developed an MR-based BCI system, but with a focus on robotic device control rather than communication systems like spellers. Their system utilizes P300 signals and integrates a real-time live view of a mobile manipulator to enhance control accuracy, showing that MR can also be applied effectively in robotics by allowing users to control complex devices through brain signals. In a similar vein, Wang et al. [19] introduced a 3D Green Virtual Face P300 spelling paradigm based on MR, illustrating the growing trend of integrating BCI systems with XR technologies. However, the study also highlights the necessity for further exploration into user comfort and the scalability of such systems in real-world applications.

There are also studies that have investigated the use of BCI systems in VR environments combined with HMDs, using control signals such as P300, SSVEPs or motor imagery (MI) [20–22]. Findings from several studies indicate that the performance of a VR-based BCI is comparable to or even better than of a traditional computer-based BCI [20,23,24]. Kathner et al. [20] examined a P300-based speller system to compare the accuracy of HMD devices with conventional screens. The results showed that VR devices could achieve similar accuracy to traditional displays, with comparable online spelling performance (96 % vs 95 %), while also enabling fast P300-BCI communication in VR environments. Also, Cho et al. [23] explored neurofeedback (NF) in a VR setting and found that VR significantly improved focus and concentration. Participants reported that while training with a desktop monitor was often tedious, using a HMD enhanced motivation and engagement.

Recently, AR with HMDs have been used to replace traditional screens in SSVEP and P300 BCI applications [15]. This has resulted in more user-friendly and portable BCIs, improving flexibility and mobility. In this setup, stimuli and objects coexist within the same field of view, allowing for more intuitive control of external devices, offering an immersive experience.

All these studies conclude that integrating BCI with XR applications can enhance the sense of immersion. Besides, XR appears to accelerate the learning process for BCI and improve user performance by increasing motivation [25]. Within the realm of XR, our study will focus on MR due to its superior potential for immersive and interactive applications. MR provides a more natural and flexible framework, enabling dynamic, real-time interactions between physical and virtual elements. MR stands out for its ability to provide immersion without disrupting the user's connection to the physical world, offering a crucial advantage for practical applications where awareness of the real environment is essential, such as in safety, navigation or collaborative interactions. In contrast, the complete disconnection of VR systems with the physical environment can be a barrier for scenarios requiring synchronization with the real world, often leading to challenges in user comfort and adaptation. Similarly, AR systems reliance on overlaying virtual elements lacks the depth of interaction and immersion that MR can achieve. By seamlessly merging virtual and physical elements in real time, MR emerges as the most promising option to overcome the limitations of AR and VR, offering greater versatility and paving the way for scalable and practical applications in real-world contexts. For instance, MR combined with BCI systems could enable both assistive and non-assistive applications. In assistive contexts, individuals with severe motor impairments could control smart home devices (such as lights, doors, or appliances) and communicate through virtual keyboards or symbol grids. In non-assistive scenarios, MR-BCI systems could support immersive gaming, hands-free control in virtual workspaces or adaptive training simulations that respond to users' cognitive states, offering enhanced engagement and usability in diverse real-world settings. However, no studies have been conducted that combine MR with c-VEP-based BCI systems, despite the fact that this control signal has demonstrated the ability to achieve high accuracy and selection speeds.

Visual fatigue is a pressing issue in c-VEP-based BCI applications [26]. Continuous exposure to changes in luminance can sometimes be uncomfortable for users in XR environments [27]. Given that accuracy rates are already remarkably high, the next step is to enhance user comfort. In this regard, several studies in XR combined with SSVEPs have examined how different characteristics of visual stimuli can affect system performance, such as color, size and brightness levels [28,29]. However, similar research has yet to be conducted for c-VEP stimuli in XR environments, leaving a gap in understanding how these immersive setups impact visual fatigue. Comfort and ease of use are critical factors for the acceptance and success of BCI applications. Therefore, investigating how immersive environments impact visual fatigue levels compared to non-immersive setups is not only relevant but essential for optimizing user experience. Understanding whether these environments induce more, less or the same level of visual fatigue will enable the development of effective strategies to mitigate this issue and ensure a more comfortable and sustainable interaction with BCI technologies.

Hence, the present study has a twofold purpose: (i) to assess the feasibility of integrating a c-VEP-based BCI into a MR environment, and (ii) to compare the visual fatigue induced by c-VEP stimuli between the MR environment and a traditional screen setup. To accomplish this, a MR application utilizing c-VEPs has been designed, developed and evaluated on 20 healthy users. This novel approach not only explores technical feasibility but also directly responds to the need for more usable, comfortable, and context-aware BCI systems. It represents the first evaluation of integrating a c-VEP-based BCI system with MR, exploring its effectiveness and comparing visual fatigue between MR and conventional screen.

This novel approach represents the first evaluation of integrating a c-VEP-based BCI system with MR, exploring its effectiveness and comparing visual fatigue between MR and conventional screen.

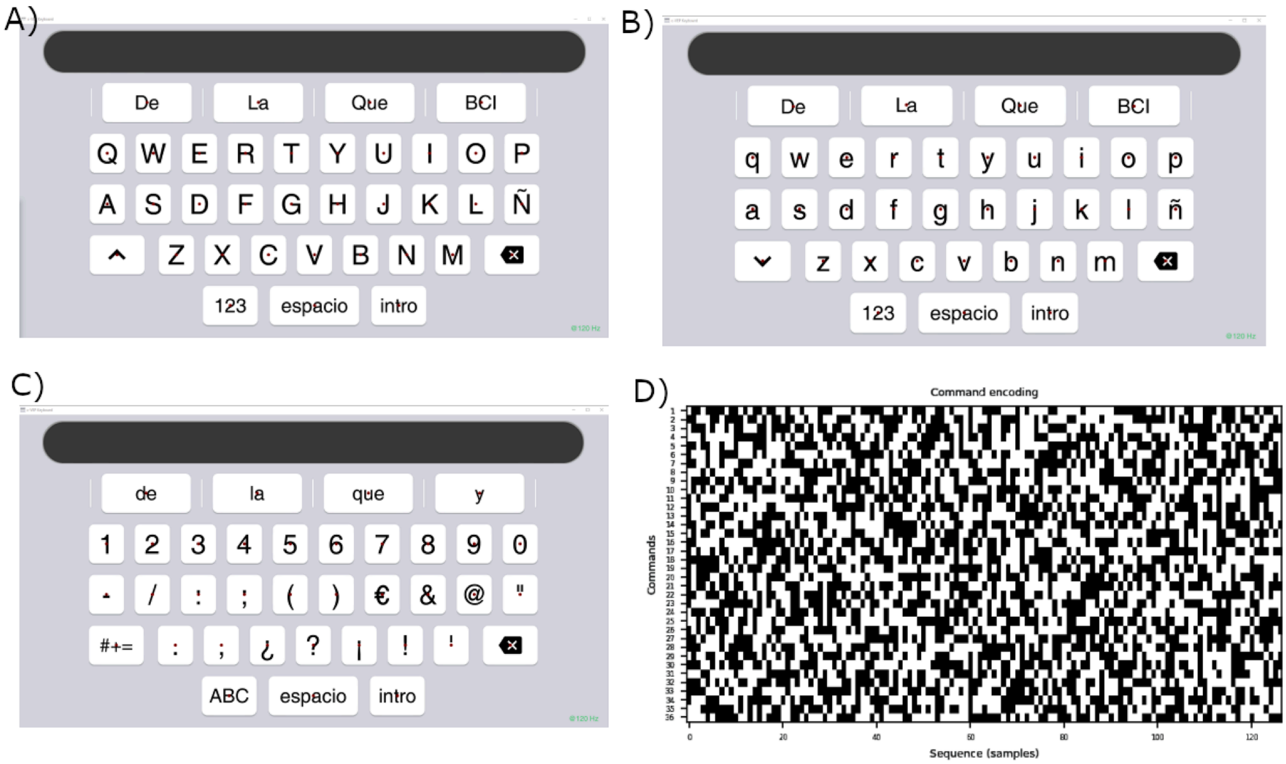

Fig. 1. (A), (B) and (C) Different speller matrices for the conventional screen condition. (D) The shifted versions of the m-sequence corresponding to each command.

2. Methods

2.1. Subjects

A total of 20 healthy users (aged 27 ± 2.70 years, 8 females and 12 males) participated in the experiments. Among the participants, 13 had prior experience with controlling BCI systems and 3 had previous experience using XR headsets. All participants provided informed consent to participate in the study.

2.2. Signal acquisition

EEG data were recorded using g.USBamp amplifier (*g.Tec*, Guger Technologies, Austria), with a sampling rate of 256 Hz. Sixteen electrodes were placed on the scalp at positions F3, Fz, F4, C3, Cz, C4, CPz, P3, Pz, P4, PO7, PO8, POz, Oz, I1 and I2, using the right earlobe as reference (A2) and grounded on AFz, in accordance with the International System 10-10 [30]. The equipment was attached to a PC Intel(R) Core(TM) i7-10700F CPU@ 2.90GHz, 32 GB RAM. The display devices used were (i) a Keep Out XGM24F + 23.8" LED FullHD FreeSync monitor with a maximum refresh rate of 144 Hz, and (ii) Meta Quest 3 (Meta Platforms, Inc) headset, set at 120 Hz. The acquisition, processing and application stages of the BCI system have been implemented within MEDUSA© software ecosystem [31]. The signal acquisition was performed employing the lab streaming layer (LSL) protocol.

2.3. Application

The application stage is responsible for interpreting the selected commands and providing real-time feedback to the user. This application consists of a 36-command keyboard designed in a QWERTY-style layout. As can be observed in Fig. 1(A)–(C), three different matrices with various commands can be selected. The keyboard initially displays the uppercase matrix on the screen. By selecting the ‘caps lock’ command, users can toggle between uppercase and lowercase matrices. Additionally, selecting the ‘123’ command shows a matrix containing numbers and special commands. Users can return to the previous matrix at any time.

The keyboard also includes delete and enter commands, with the latter used to submit the text and clear the input field. At the top of the screen, four items were included to assist with typing, either through the autocomplete function or through suggestions. If the system detects that a word is being typed, it suggests words that start with those characters. To implement this functionality, a 1-gram of the 1000 most common Spanish words was collected and sorted according to frequency of use. An n-gram is a contiguous sequence of n items (usually words) used in statistical language processing to predict the next word in a given context [32]. In our application, this concept is utilized through 2-gram, 3-gram and 4-gram models, which include the 100,000, 80,000 and 80,000 most common combinations in Spanish, respectively. The 2-gram model predicts the next word based on the current word, while the 3-gram uses the previous two words, and the 4-gram considers the last three words. These n-grams were generated by analyzing extensive text corpora in Spanish, where the frequency of individual words and word sequences was calculated. The data was then processed to create dictionaries that map sequences of $N-1$ words to their most likely subsequent words, allowing the system to efficiently predict and suggest words in real-time based on the user’s input.

The graphical interface was developed using Unity, a game engine that employs the C# programming language. Unity was selected for its seamless integration with XR devices and its ability to control each monitor refresh frame. Precise stimulation timing is essential for c-VEPs, as even minor variations in latency can lead to decoding errors [8]. Communication between the graphical interface and the processing stage was established through a bidirectional full-duplex TCP/IP client-server architecture [31]. The codification of the keyboard commands is achieved using a binary maximum length sequence (m-sequence) consisting of $N = 127$ bits. This sequence is generated by a linear feedback shift register (LFSR) initialized with the state 1100000 and using base 2 (i.e., 0 white stimulus, 1 black stimulus) with an order of 7 [33]. Fig. 1(D) displays the command matrix encoding based on this sequence. The sequence exhibits a flat autocorrelation function, being 1 for the original signal and $-1/N$ for all other shifts [8].

Each selection matrix consists of 36 commands, each corresponding to a specific character that can be selected. While the sequence used has a flat autocorrelation, this does not guarantee that the EEG response will exhibit the same property. To improve the decoding process, the assigned delays were distributed as widely as possible across the 127-bit sequence [8]. To encode the different commands, the original m-sequence was time-shifted by of $\theta_i = 4 \cdot i$, where $i = 0, 1, \dots 35$. A genetic algorithm was utilized to ensure that commands with consecutive delays were not placed adjacently.

2.4. Processing stage

The signal processing stage is based on the standard processing pipeline for the c-VEP circular shifting paradigm, as detailed by Martínez-Cagigal et al. [8]. Initially, the processing stage begins with the pre-processing of the EEG signal, focusing on removing frequency bands that are not relevant to c-VEP detection. EEG signals were pre-processed using a series of 7th-order infinite impulse response (IIR) Butterworth filters. Initially, a notch filter at 50 Hz was applied to eliminate power line interference. Subsequently, a filter bank composed of three bandpass filters was employed, covering frequency ranges of 1–60 Hz, 12–60 Hz and 30–60 Hz. This approach aligns with the methodology proposed by Gembler et al. [34], where the use of specific and overlapping frequency bands was demonstrated to optimize signal-to-noise ratio (SNR) and improve the real-time decoding of user commands. Following the filtering process, canonical correlation analysis (CCA) was applied in each trial to decode the user's intended target command in real-time. In this stage, two phases are distinguished: calibration and testing. During the calibration process, the signal is recorded while the user directs their attention to the command encoded with the original m-sequence (i.e., without delay) for k numbers of cycles (i.e., repetitions of the m-sequence). Two versions of the EEG response were obtained after preprocessing: (i) the concatenated epochs $\boldsymbol{A} \in \mathbb{R}^{kN_s, N_c}$ (i.e., N_s is the number of samples and N_c the number of channels); and (ii) the epochs averaged over all cycles $\boldsymbol{B} \in \mathbb{R}^{kN_s, N_c}$ repeated k times to match the dimensions. CCA was applied to maximize the correlation between $\boldsymbol{A}$ and $\boldsymbol{B}$. The spatial filter, $\boldsymbol{w_b}$, is selected as the projection that maximizes the correlation coefficient between these two versions. Consequently, the main template was calculated by projecting the averaged response using the CCA-trained spatial filter. Three main templates were obtained, one for each filtered signal from the filter bank. Templates for the rest of the commands were generated by circularly shifting the main template according to each lag [8].

Additionally, we have addressed non-stationary artifacts that could negatively impact model performance, such as blinking or electrode-pops. During the calibration process, the standard deviation (σ_A) of each channel's data in the concatenated epochs is calculated. Artifacts are identified within a cycle if the standard deviation of that epoch exceeds three times σ_A. Only epochs without artifacts on any channel were used to calibrate the system [35].

Subsequently, in the online mode, the epochs of each trial are extracted and spatially projected with the spatial filter $\boldsymbol{w_b}$. The response of the trial is then compared against all templates corresponding to each filtered signal, resulting in a vector that contains the Pearson's correlation coefficients for each command. The average correlation across the entire bank of filters is computed. Then, the command selected would be the one associated with the maximum coefficient [35].

2.5. Experimental protocol

In order to evaluate the feasibility of using MR with c-VEPs, both quantitative and qualitative metrics were analyzed. Firstly, two metrics were employed: (i) accuracy (%), quantifying the percentage of correctly classified selections among all predicted selections; and (ii) ITR (bits/min), parameter that offers an objective assessment of the system's information transfer rate [1]. The ITR was calculated using the following formula:

$$ITR\left(\frac{bits}{min}\right) = Q \cdot \left[log_2 S + P \cdot log_2 P + (1-P) log_2 \left(\frac{1-P}{S-1} \right) \right], \tag{1}$$

where Q denotes the number of selections per minute, P represents accuracy and S the number of commands [36]. Additionally, a qualitative evaluation was conducted by means of questionnaires such as system usability scale (SUS) and eyestrain test.

The experiment was conducted in a single session lasting approximately 55 min. Each session included a series of tasks with a total duration of 45 min. Tasks were performed under two conditions: (i) MR; and (ii) conventional screen. Participants were seated during both conditions to ensure consistent EEG signal acquisition and to minimize motion-related artifacts. They were required to make the same selections in both conditions and were instructed to focus their attention on selecting the corresponding commands without getting distracted. The same application was used for both MR and conventional screen conditions, with the order of these conditions randomized across participants to avoid bias. In the MR condition, the default gray background was replaced with the passthrough feature of the Quest 3, which provides a real-time, visually immersive 3D view of the physical environment through the Meta Quest headsets. The background in this condition was a monotone wall, similar to conventional screen setup. This configuration remained consistent throughout the experiment to ensure that visual performance was not influenced by variations in contrast or brightness of the background in the MR environment.

Each condition included both calibration and online stages. It is important to note that a refresh rate of 120 Hz was used for both conditions. This higher frequency, compared to the standard 60 Hz, was chosen to improve system responsiveness and user comfort, as supported by previous studies [11,35]. Consequently, the duration of a complete cycle of the sequence was 1.05s (i.e., 127/120). The calibration stage was crucial for establishing the c-VEP templates specific to each user. These templates are used to identify the selected command during the online phase. Participants were instructed to look at the letter 'P', which corresponds to the command encoding the original m-sequence without lag. This phase had a duration of 105s, corresponding with 2 runs of 5 trials each, so 100 cycles (10 cycles per trial) were recorded. Following this, a decoding model was trained using the signal processing pipeline detailed in Section 2.4.

The next step involved conducting online tasks, where all users were asked to select the same set of predefined content, consisting of both individual words and short phrases (e.g., "NEURONAS", "CEREBRO", "HOLA QUE TAL"). Fig. 2 displays a screenshot showing the command matrix with their corresponding flashes in both conditions. Each command required a selection time of 10.50s, corresponding to 10 established cycles. The experiment consisted of 6 runs, with 5 to 8 trials per run and 10 cycles per trial. This amounted to a total of 41 selections. Notably, if a participant accidentally selected a wrong command, they were instructed to proceed to the next character without correcting the mistake. The autocomplete function or through suggestions was not employed during the experiment to ensure that it did not influence the number of selections.

After completing all the tasks, users were asked to fill out questionnaires to assess eyestrain and usability. The usability of the application was evaluated using a SUS questionnaire, consisting of 10 alternating positive and negative statements to reduce acquiescence bias [37]. Participants rated their answers on a 5-point Likert scale [38]. Furthermore, the last item invited them to offer suggestions for improving the application. The eyestrain test consisted of 8 questions, also using a Likert scale. This test included two additional final questions aimed at evaluating visual fatigue on a scale from 1 to 10 under each condition.

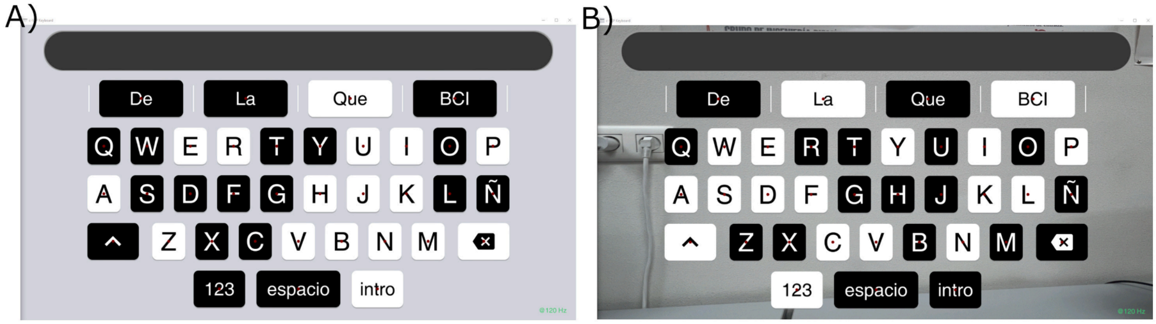

Fig. 2. (A) Screenshot of the speller with its corresponding flashes with a gray background for the conventional screen condition and (B) HMD view with passthrough for the MR condition.

The additional resources, including data, code, and methodological information, can be made available upon reasonable request, in accordance with ethical guidelines.

3. Results

The accuracy and ITR analysis consisted of examining the results of the spelling tasks completed by users under both conditions. Table 1 details the average accuracies and ITRs of each user for each type of condition, based on 10 cycles. The average accuracies for MR and conventional screen were 96.71 % and 95.98 %, respectively. In terms of ITR, the MR condition achieved a maximum value of 27.55 bits/min, whereas the screen condition recorded 27.10 bits/min. The number of selections per minute was determined to be 5.7. This selection time was calculated excluding pause times, considering that 10 cycles were used, with each cycle lasting 10.50s. Fig. 3 also displays the accuracy for each user for each cycle in both conditions. We can observe that some users achieved their highest accuracy with fewer cycles, which could translate into a shorter selection time. For MR condition, an average accuracy of 92.57 % was observed with just 5 cycles, whereas for the conventional screen condition, the average accuracy was 89.55 % with the same number of cycles, as shown in Table 2. A Wilcoxon signed-rank test was employed for the statistical analysis. The results revealed no significant differences in accuracy between conditions (p-value > 0.05) for any number of cycle. For the ITR, no significant differences were found between the two conditions for each cycle (p-value > 0.05). Unfolded accuracies and ITR for each user and cycle are detailed in the supplementary material.

Table 1
Accuracies and ITRs by all users for each condition.

User	Mixed reality		Conventional screen	
	Accuracy (%)	ITR (bits/min)	Accuracy (%)	ITR (bits/min)
U01	100.0	29.31	100.0	29.31
U02	92.68	25.04	85.37	21.65
U03	100.0	29.31	100.0	29.31
U04	100.0	29.31	100.0	29.31
U05	100.0	29.31	100.0	29.31
U06	80.49	21.65	92.68	25.04
U07	100.0	29.31	97.56	27.66
U08	100.0	29.31	97.56	27.66
U09	95.12	26.30	92.86	25.13
U10	100.0	29.31	100.0	29.31
U11	100.0	29.31	92.68	25.04
U12	100.0	29.31	75.61	17.67
U13	100.0	29.31	97.56	27.66
U14	92.68	25.04	95.12	26.30
U15	95.12	26.30	100.0	29.31
U16	82.93	20.61	100.0	29.31
U17	100.0	29.31	100.0	29.31
U18	100.0	29.31	92.68	25.04
U19	95.24	26.36	100.0	29.31
U20	100.0	29.31	100.0	29.31
Average	**96.71**	**27.55**	**95.98**	**27.10**
SD	**5.63**	**2.69**	**6.08**	**3.05**

SD: Standard deviation. Ten cycles were utilized.

Table 2
Average accuracies achieved by all users as a function of the number of cycles for both conditions, their corresponding p-values and time per cycle.

Nº Cycles	Selection Time	Accuracy		p-value
		MR	Screen	
1	1.05 s	49.72 %	44.37 %	0.57
2	2.10 s	76.39 %	68.85 %	0.23
3	3.15 s	83.45 %	79.46 %	0.62
4	4.20 s	88.80 %	86.87 %	0.88
5	5.25 s	92.57 %	89.55 %	0.14
6	6.30 s	93.18 %	90.63 %	0.26
7	7.36 s	95.13 %	92.70 %	0.20
8	8.40 s	95.01 %	94.27 %	0.97
9	9.46 s	96.11 %	95.62 %	0.85
10	10.50 s	96.71 %	95.98 %	0.67

In Fig. 4, the grand-averaged VEPs of the users for the two conditions at channel Oz can be observed over a cycle duration (1.05 s). Moreover, a topographic plot was generated weighting the contribution of each electrode in the spatial filter. This is depicted in Fig. 5 for all users across both conditions.

Regarding subjective items, the statements were evaluated on a scale from 1 (strongly disagree) to 5 (strongly agree). Table 3 presents the statements and their numerical values collected from all users in the SUS questionnaire. On the other hand, Table 4 presents the mean values obtained from the eyestrain questionnaire for the different statements. The odd statements referred to positive aspects while the even address negative ones. In addition, two questions were included, assessing overall visual fatigue for each condition from 1 to 10. The average visual fatigue score was 4.60 for the conventional screen condition, compared to 3.45 for the MR condition. No statistically significant differences (p-value > 0.05) were observed between conditions. To facilitate future comparisons with similar studies, all individual responses and per-subject averages for both questionnaires have been made available in the supplementary material.

4. Discussion

4.1. Performance

The first objective was to determine whether the integration of MR with c-VEPs enables the development of a reliable BCI system. To address this, metrics such as the overall accuracy across all tasks and ITR have been calculated. The results confirm the feasibility of this integration, as a high overall accuracy of 96.71 % was achieved, well above the 70 % threshold for a controllable BCI system [3]. Moreover, as

Table 3
Results of questionnaire SUS for all users. Each statement was rated on a 5-point Likert scale, where 1 means strongly disagree and 5 strongly agree.

	Statements	Mean score ± SD
1.	I found it interesting to learn about and use this BCI system.	4.95 ± 0.22
2.	The design of the user interface is unattractive and non-functional.	1.60 ± 0.73
3.	The visual quality and experience are satisfactory.	4.60 ± 0.58
4.	The system requires too much concentration.	2.40 ± 1.06
5.	The process of configuring and calibrating the system was clear and efficient.	4.95 ± 0.22
6.	I have experienced visual fatigue or dizziness related to any of the conditions.	2.15 ± 0.91
7.	The application responds quickly and smoothly.	4.70 ± 0.46
8.	I have had difficulties with command selection.	1.60 ± 0.86
9.	I would be willing to participate in a study of this nature.	4.90 ± 0.30
10.	The duration of the session seemed too long.	1.60 ± 0.86

SD: Standard deviation.

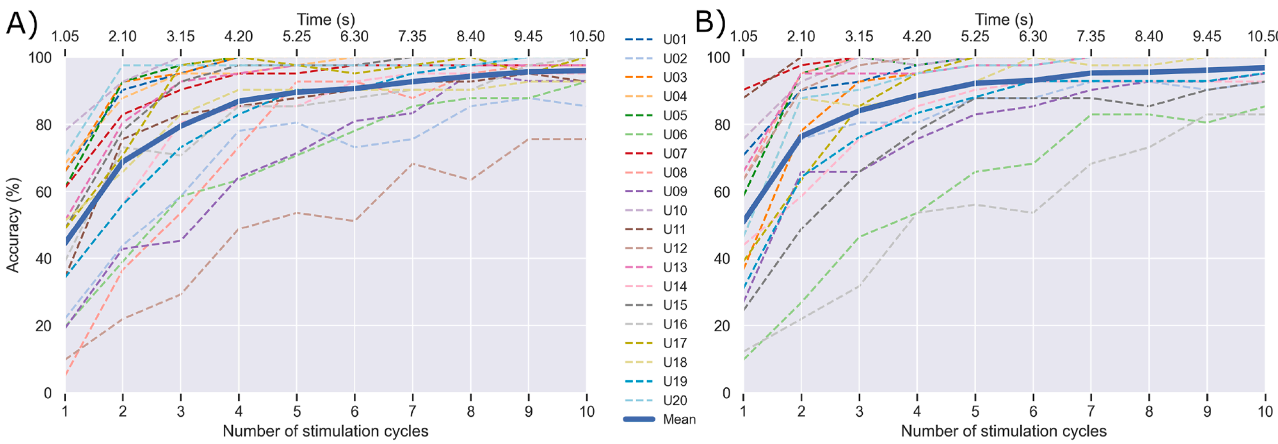

Fig. 3. Performance of each user in function of the number of cycles for (A) conventional screen and (B) MR condition.

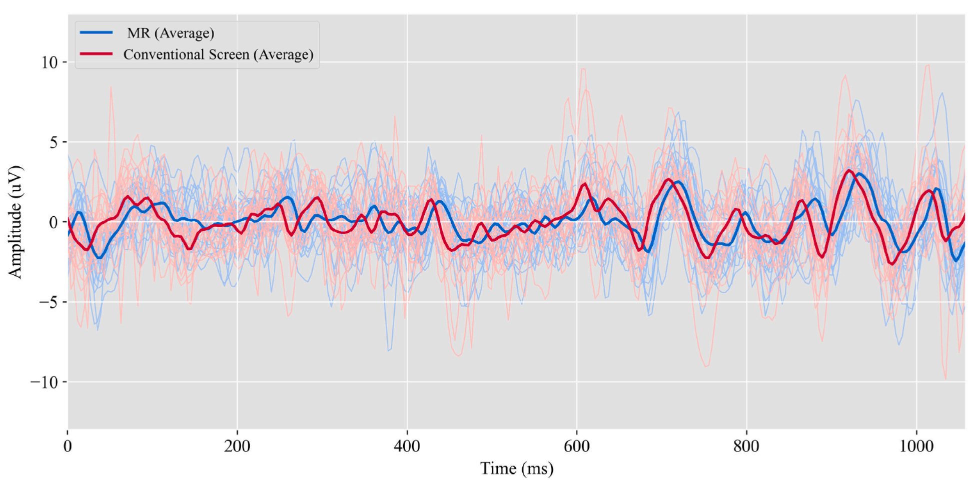

Fig. 4. Grand-averaged and individual visual evoked potentials (VEPs) of all users for 2 conditions.

mentioned above, high accuracy rates exceeding 95.0 % were achieved for both conditions, with 95.98 % for the conventional screen and 96.71 % for the MR condition, further demonstrating the system's effective performance. No significant differences were found between the two conditions, suggesting that a c-VEP-based BCI system can be reliably used in MR environments.

Furthermore, it is noteworthy that a trend of slightly lower accuracy for tasks involving conventional screens compared to those performed in MR was observed, although this difference is not statistically significant for any number of cycles (p-value > 0.05), as shown in Table 2. This discrepancy may be attributed to the fact that the HMD narrows the field of vision and that the larger size of the commands displayed in MR could have affected both concentration and precision in task execution. Additionally, some studies support that XR can enhance user engagement and immersion and thereby improve the accuracy of BCI [39].

Regarding the evolution of accuracy based on the number of cycles, Fig. 3 shows that, in the case of the MR condition, some users required a minimum number of cycles to reach maximum accuracy. As presented in Table 2, the average accuracy for all users reached 92.57 % after 5 cycles. These findings suggest that the average number of cycles could be reduced to five while still maintaining a high level of accuracy. This reduction would drastically decrease the selection time from 10.50s (10 cycles) to 5.25s (5 cycles).

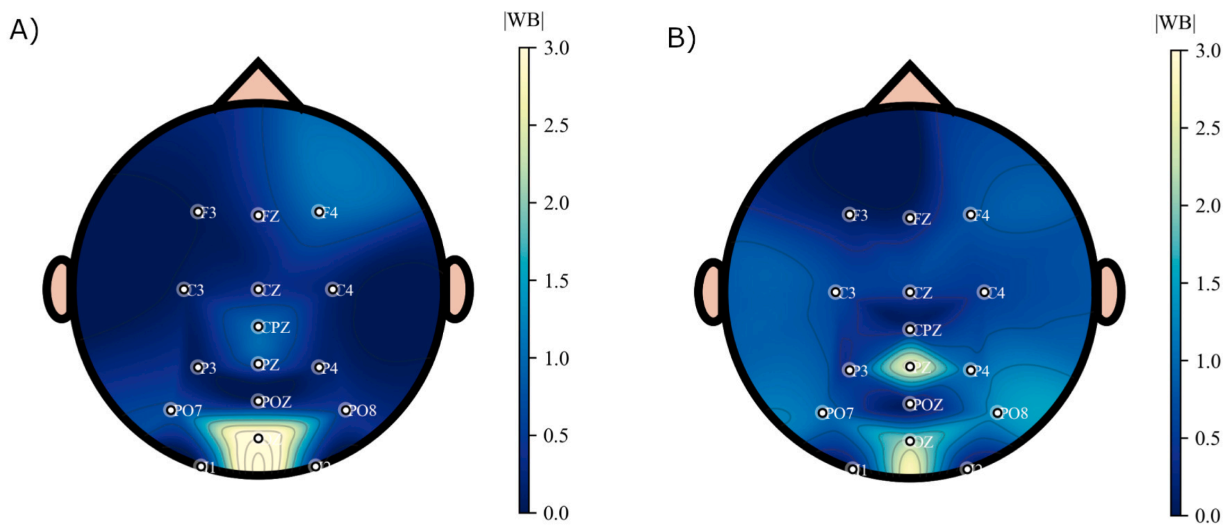

Fig. 5. (A) Topographic plot for all users in MR condition. (B)Topographic plot for all users in conventional screen condition. $\boldsymbol{w}_b$ is the spatial filter that represents the importance of each electrode.

It is also noteworthy that some users achieved low accuracy with few cycles. In the case of the conventional screen condition, particular attention should be given to the low accuracies observed in participant U12, who indicated in the questionnaires a preference for using MR and reported greater ease in selection with these systems. For the MR condition, low accuracy was observed in a few cycles for users U06 and U16. Both participants were not familiar with the use of XR and participant U16 had no prior experience with BCI systems, which could have influenced their results. In particular, user U06 reported experiencing some dizziness while using the HMD. This symptom is indicative of a common side effect known as motion sickness among XR users [40]. This discomfort might have impaired their ability to maintain concentration and, consequently, affected their precision in selecting commands. The lack of familiarity with these technologies, coupled with side effects such as dizziness, likely could contributed to the need for more cycles to achieve greater accuracy.

Regarding the ITR, maximum values of 27.55 bits/min were recorded for the MR condition and 27.10 bits/min for the conventional screen condition. The absence of significant differences indicates that the type of presentation, whether MR or conventional screen, does not have a substantial impact on the ITR.

4.2. Brain responses

Analyses of brain responses have yielded interesting results. Firstly, despite using the same m-sequence for stimulus presentation in both conditions, the VEPs associated with each condition exhibited some differences, although they share a similar morphology (Fig. 4). Additionally, it is observed that the signal appears to be of delay from one condition to another. This phenomenon may be attributed to the fact that MR requires more graphical and computational processing than a conventional screen, which can overload the system and affect the synchronization of EEG signals. Additionally, real-time rendering in MR to create an immersive experience consumes more resources, potentially increasing the delay in tagging stimuli onsets.

Moreover, as illustrated in Fig. 5, the topographic plot reveals that the most discriminative channel was Oz. Specifically, the occipital channel exhibited the highest activity, corresponding to the primary visual cortex (V1), where the c-VEP response is most intensely received. However, VEPs are also observable over the parietal cortex [41], as can be seen for conventional screen condition. The difference in parietal activation between using a traditional screen and MR could be attributed to the distinct ways each medium presents visual information. Conventional screens might engage the parietal cortex more due to the need to process and locate objects within a flat, static visual space, given that the parietal cortex is a component of the dorsal visual pathway responsible for encoding spatial location [42]. In contrast, MR provides a more immersive three-dimensional experience, potentially simplifying visual processing and thereby reducing activation in the parietal cortex. Individual topographic plots for both conditions are included in the supplementary material.

4.3. Usability metrics

The results of the SUS questionnaire, obtained after applying the SUS scale, indicate a high usability of the system, with an average score of 85.87 ± 8.34 points. This suggests that users generally found the system easy to use and effective in both conditions. Moreover, a score exceeding 68 would be considered above average [43]. The lowest total score in a user was 67.5 points, indicating a generally positive reception among users and affirming that the overall quality and user experience were satisfactory. The highest-rated aspects were the interest in learning about and using the system, as well as the clarity and efficiency of the configuration and calibration process. Conversely, the aspect that received the lowest rating was the system's requirement for a high level of concentration, which some users reported could lead to fatigue with prolonged use and complicate command selection. This suggests that the interface should be adapted to individual user characteristics. For instance, users could have the option to adjust the distance of the virtual keyboard, either bringing it closer or moving it farther away as needed. Such adjustments could help reduce cognitive load, making the system more comfortable to use and less tiring overall. Additionally, with regard to visual fatigue, a few users reported experiencing mild dizziness related to MR [40], while others experienced dryness of the eyes when using the conventional screen.

Overall, these findings have significant implications for the future design of the system. Enhancing ergonomics and reducing cognitive load could further improve usability and user satisfaction. Addressing issues of motion sickness and making the interface more intuitive and customizable could increase system adoption and effectiveness across various use contexts.

4.4. Eyestrain test

Eight statements from the eyestrain test were presented to assess visual fatigue in Table 4. The first statement addressed whether the

Table 4
Results of questionnaire of eyestrain for all users. Each statement was rated on a 5-point Likert scale, where 1 means strongly disagree and 5 strongly agree.

	Statements	Mean Score ± SD
1.	The immersion provided by MR enhances my overall experience with the application.	4.00 ± 1.02
2.	I have experienced visual fatigue or dizziness related to MR use.	2.90 ± 1.11
3.	I felt comfortable using the application with the MR device.	4.10 ± 1.10
4.	The use of passthrough seems more distracting than helpful to me.	3.60 ± 1.29
5.	I prefer using the application with MR rather than viewing it on a screen.	3.80 ± 1.36
6.	I find the stimuli very annoying.	2.40 ± 1.35
7.	I found it easier to select commands using MR, which also helped my eyes feel less fatigued.	3.10 ± 1.24
8.	Gradually, I had to put in a lot of effort to see better.	2.20 ± 1.18

SD: Standard deviation.

immersion provided by MR enhanced the overall experience, where most participants responding positively. It is important to note that a MR system was utilized, incorporating passthrough technology that allowed users to see their physical environment along with the speller and selection commands.

The second statement addressed visual fatigue or dizziness associated with MR [40]. Although this issue occurred for a few users, it was not widespread in this study. Participants who experienced dizziness might have been more affected by MR due to differences in their vestibular systems or limited experience with these systems [44]. These factors could have heightened their discomfort during the session. Even so, the experiment had a short duration (< 1 h), which likely minimized the possibility of developing such symptoms.

The third statement evaluated the comfort of using the speller with the MR device. Despite the HMDs being adjustable via straps and having a certain weight, users reported no discomfort.

Statement 4 focused on the impact of using a real background in MR (passthrough) on the user experience. In the study by Riechmann et al. [45], it was observed that incorporating a real background significantly reduced classification accuracy in a BCI system based on c-VEPs. Although their study did not involve XR, it reported a notable decrease in performance: without a background, the system achieved 65 % accuracy while with a background, accuracy dropped to 50 %. In our study, although some users reported distraction from seeing the real background of the environment (passthrough) while selecting different characters, no significant differences in performance were observed. In fact, there was a trend toward higher accuracies with MR compared to conventional screen, which could be attributed to greater user engagement and immersion with the MR environment.

Regarding the preference for using MR over a conventional screen, as addressed in statement 5, only 4 users preferred the conventional screen, while 5 users had no strong preference and 11 users favored the MR experience. Statements about annoying stimuli, such as flickering and the need to make more visual effort to see better over time were also made (statements 6 and 8). Although this is more evident in longer-term evaluations, it could be a relevant effect that directly impacts accuracy. However, in this case, low values were obtained. Subjective opinions about the lesser difficulty of selection using MR (statement 7) were consistent with the obtained accuracy, showing a slight tendency.

The last two additional statements focused on assessing visual fatigue produced by each condition. While no significant differences were found (p-value > 0.05), there was a slight indication of higher levels of eyestrain among participants for the screen condition (3.45 compared to 4.60). This suggests that a BCI based on c-VEPs with MR would be feasible since the MR condition did not produce significantly more visual fatigue compared to the conventional screen condition. Furthermore, the slightly lower eyestrain in MR highlights its potential for providing a more comfortable user experience over extended periods, making it a promising platform for BCI applications.

4.5. Comparison with other studies

No studies have focused specifically on communication with spellers using BCI-MR for any control signals. Therefore, a comparative analysis was conducted between spellers implemented using VR and different control signals (P300 and SSVEPs) (Table 5). No studies using XR with c-VEPs have been found.

Firstly, Kathner et al. [20] investigated a speller system based on visual P300 ERP to determine if comparable accuracy levels could be achieved with HMD devices versus conventional screens. For their virtual keyboard, a 5×5 matrix was displayed, consisting of all the letters of the alphabet except for the letter Z. They evaluated 18 healthy users, achieving an accuracy of 94.00 % and an ITR of 16.20 bits/min with only three flash sequences during online spelling across a total of 8 sessions. Additionally, a person with locked-in syndrome (LIS) successfully controlled the system, achieving 100 % accuracy in one session. Regarding potential improvements, it is evident that the ITR was notably low. Furthermore, usability issues were identified, including concerns about HMD's quality and resolution. In addition, the device's weight may cause discomfort during extended use, as highlighted in our study.

On the other hand, the study conducted by Grichnik et al. [46] evaluated a VR-based hybrid BCI utilizing SSVEPs and gesture input, achieving an accuracy of 91.11 % and an ITR of 23.56 bits/min. The proposed interface consisted of three flickering boxes arranged horizontally, each containing 9 letters or symbols. In total, all 27 letters of the alphabet and one symbol were displayed. When a user focused on a box, its contents split among the three boxes, narrowing down the choices. After selecting on the third screen, the chosen letter was typed and the interface reset. Users could also use head gestures to delete or go back.

Table 5
Summary of comparison with other spellers using VR and different control signals.

Study	Year	Control Signal	No. Healthy Users	Accuracy	ITR	No. Classes
Kathner et al. [20]	2015	P300	18	94.00 %	16.20 bits/min	25
Grichnik et al. [46]	2019	SSVEPs + gesture input	18	91.11 %	23.56 bits/min	4
Yao et al. [47]	2018	SSVEPs	3	82.40 %	287.00 bits/min	4
Present study	2025	c-VEPs	20	96.71 %	27.55 bits/min	36

ITR: information transfer rate, SSVEPs: steady-state visual evoked potentials, c-VEPs: code-modulated visual evoked potentials.

Also, Yao et al. [47] proposed a 40-class BCI speller in VR based on hybrid gaze controls using eye tracking and SSVEPs. The virtual keyboard consisted of 40 targets, including the 26 letters of the English alphabet, 10 numeric digits (0–9) and 4 additional symbols. This keyboard was organized in a 4×10 matrix and the character selection was carried out in two distinct stages: first, eye tracking was used to select a block of 4 characters from the 40 available; then, within the selected block, a 4-class SSVEP system was employed to identify the specific target. Their online experiments with three users achieved an average ITR of 360.7 bits/min with an average accuracy of 95.20 %. Additionally, an offline analysis was performed using only SSVEPs, achieving an average accuracy of 82.40 % and an ITR of 287 bits/min.

In contrast to these findings, participants in our study reported high usability and low levels of visual fatigue in both conditions, highlighting a notable distinction in user comfort compared to the discomfort identified in previous research. Furthermore, our study achieved high accuracy using only the c-VEP signal, whereas two of the mentioned studies relied on hybrid BCI systems to achieve similar accuracy levels. Regarding keyboard design, our study featured 36 commands, enabling users to select effectively type any word, number or symbol. It also differentiated between uppercase and lowercase letters and included a larger number of symbols. Additionally, a delete command button was provided and users could also return to the previous interface without needing gesture input, which could introduce noise into the signal during movement. The design also included autocomplete and suggestions features, enhancing communication and command selection. Overall, these features demonstrate that our study provides a more effective and comfortable solution for BCI communication than those previously reported.

Nevertheless, direct comparisons should be interpreted with caution due to the substantial differences in experimental setups, including control paradigms, interface designs, and evaluation protocols. Each control signal (e.g., P300, SSVEP, c-VEP) imposes distinct constraints and processing requirements, which can significantly impact reported metrics such as accuracy and ITR. As a result, the variability across studies limits the extent to which performance figures can be directly contrasted. Still, these studies collectively provide useful context for situating our work within the broader landscape of BCI research in immersive environments.

To the best of our knowledge, no other studies evaluate the accuracy and ITR of spellers in VR. Other research combining BCI and VR has focused on different applications, such as rehabilitation for neurological diseases [48] or entertainment [49].

4.6. Contributions

This study introduces a BCI system that, for the first time, integrates c-VEPs with MR, demonstrating the feasibility of using cVEPs in immersive environments. Our findings reveal that the MR condition achieved an accuracy of 96.71 %, performing on par with the traditional screen-based condition (95.98 %), without significant differences. Furthermore, the MR condition exhibited robust performance metrics, including accuracy and ITR, alongside high usability scores, validating the suitability of cVEP-driven systems for MR applications. Importantly, both conditions reported low levels of visual fatigue, as assessed by an eyestrain test, ensuring a comfortable and user-friendly experience. These contributions position our system as a significant step forward in the integration of BCI technologies with MR environments.

4.7. Limitations and future work

After this discussion, we consider that the feasibility of integrating c-VEPs into MR has been demonstrated. However, there are aspects that can be improved in future studies.

Notably, despite demonstrating effectiveness among healthy users, it is crucial to assess its application among individuals with severe motor disabilities. This demographic has historically been the principal focus of BCI systems designed for communication and control purposes. Thus, further studies with this target group are recommended to comprehensively assess the usability and impact of the technology.

While the current study was conducted under controlled conditions, with participants seated to ensure consistent EEG signal acquisition and reduce motion-related artifacts, future work should evaluate system performance in more dynamic, real-world scenarios. Investigating BCI operation during user movement, shifting gaze, and varying levels of physical activity will be crucial for the practical deployment of MR systems based on c-VEPs.

Furthermore, it has been observed that prolonged use of HMDs can cause the devices to overheat, potentially resulting in physical discomfort such as headaches and neck strain. Nevertheless, continuous progress in XR technologies is helping to mitigate these issues. Effectively addressing these challenges will be key to enhancing both the usability and user comfort of MR-based c-VEP systems. Notably, XR systems with integrated electrodes are beginning to enter the market, offering a potential solution to enhance user comfort and streamline BCI setups. Additionally, it would be interesting to test dry or semi-dry EEG systems, since offers a practical alternative to traditional gel-based systems, facilitating quicker setup and improving comfort for extended use [50,51].

Additionally, an objective and interesting approach to evaluating the comfort of different systems would be to monitor the progression of fatigue biomarkers, such as eye blinking frequency and the alpha-to-beta band ratio, before, during and after use [52].

The use of deep learning (DL) models for EEG processing, such as convolutional neural networks (CNNs), offers promising opportunities to enhance decoding performance and robustness to variability. These models can potentially replace traditional methods like CCA, providing faster and more accurate classification. Beyond the choice of decoding model, future work should explore the integration of asynchronous paradigms (i.e., detection without control), so that commands are issued only when the user is attentive to visual stimuli [53,54]. Additionally, implementing ‘early stopping’ techniques would be advisable. These algorithms dynamically determine the number of cycles needed to make a selection, eliminating the need to wait for all 10 predetermined cycles before making a decision. Offline analysis has demonstrated that high precision can be achieved with fewer cycles, which would significantly increase the ITR. Speed is a crucial factor in spellers, making this approach particularly important. On the other hand, it is important to note that direct performance comparisons between c-VEP and other BCI paradigms (e.g., P300, SSVEP) are inherently limited by fundamental methodological differences. These include variations in control paradigms, interface design, user interaction demands, and signal processing strategies, all of which can significantly affect performance metrics such as accuracy and ITR. Consequently, results from different paradigms should be interpreted in context.

Lastly, to improve user experience and address the potential for visual fatigue associated with high-contrast flickers, future work could explore several strategies supported by recent research. These include amplitude depth reduction (e.g., using gray instead of binary black-and-white flickers) [54], the use of non-binary m-sequences for greater visual comfort without sacrificing accuracy [11,35], and the implementation of barely visible textured stimuli along with burst c-VEP [50]. Additionally, practical adjustments such as moderating the speed of movement in MR environments, using lower-brightness stimuli [26]), and incorporating more regular breaks could further help mitigate fatigue and enhance the overall user experience.

5. Conclusion

To our knowledge, this is the first study to evaluate the integration of MR in a c-VEP-based BCI speller. The application was tested on 20 healthy participants in a single session under two conditions: MR and conventional screen. An average accuracy of 96.71 % ± 5.63 % was achieved in MR, indicating that c-VEPs are suitable for developing MR applications. On the other hand, the average accuracy obtained for conventional screen was 95.98 % ± 6.08 %. The accuracy achieved in the MR condition was consistently high across all 10 cycles, with no significant differences compared to the conventional screen condition (*p*-value > 0.05). Additionally, the maximum achieved ITR was 27.55 bits/min for the MR condition and 27.10 bits/min for the conventional screen, with no significant differences observed (*p*-value > 0.05). This suggests that MR performs at least as well as traditional screens and may even offer potential advantages, such as enhanced user engagement and a more immersive experience, reinforcing the viability of MR for similar applications.

The SUS questionnaire results from the participants indicated high usability ratings, with the majority finding the system easy to use and expressing interest in participating in the study. Furthermore, the eyestrain test revealed low levels of visual fatigue in both conditions. Based on the results of this study, the findings can provide valuable insight for the design, development and evaluation of more applications with MR-BCI based on c-VEPs.

CRediT authorship contribution statement

Selene Moreno-Calderón: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization; **Víctor Martínez-Cagigal:** Methodology, Software, Validation, Writing – review & editing; **Ana Martín-Fernández:** Writing – review & editing; **Eduardo Santamaría-Vázquez:** Software, Writing – review & editing; **Roberto Hornero:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

There is no conflict of interest.

Acknowledgments

This research was supported by the project 0124_EUROAGE_MAS_4_E, cofunded by the European Union through the Interreg VI-A Spain-Portugal Program (POCTEP) 2021-2027. This publication is part of the TED2021-129915B-I00 action, funded by MCIU/AEI/ 10.13039/501100011033 and the European Union NextGenerationEU/ PRTR. This work was supported by the Regional Goverment of Castilla y León (Junta de Castilla y León, Consejería de Educación) and the EU-FEDER under the project VA140P24. This work was supported by "Centro de Investigación Biomédica en Bioingeniería, Biomateriales y Nanomedicina (CIBER-BBN)" through "Instituto de Salud Carlos III" co-funded with ERDF funds.

Supplementary material

Supplementary material associated with this article can be found in the online version at 10.1016/j.bbe.2025.06.003

References

[1] Wolpaw JR, Birbaumer N, Mcfarland DJ, Pfurtscheller G, Vaughan TM. Brain-computer interfaces for communication and control. Clin Neurophysiol 2002;113(6):767–91. https://doi.org/10.1016/S1388-2457(02)00057-3

[2] Li Y, Pan J, Wang F, Yu Z. A hybrid BCI system combining p300 and SSVEP and its application to wheelchair control. IEEE Trans Biomed Eng 2013;60(11):3156–66. https://doi.org/10.1109/TBME.2013.2270283

[3] Martínez-Cagigal V, Gómez-Pilar J, Álvarez D, Hornero R. An asynchronous p300-based brain-computer interface web browser for severely disabled people. IEEE Trans Neural Syst Rehabil Eng 2017;25(8):1332–42. https://doi.org/10.1109/TNSRE.2016.2623381

[4] Kerous B, Skola F, Liarokapis F. EEG-based BCI and video games: a progress report. Virtual Real 2018;22:119–35. https://doi.org/10.1007/s10055-017-0328-x

[5] Rajmohan MV, Shaik CH, Gogoi RA, A. Home automation using brain computer interface (BCI). In: Int Conf Power, Energy. 2020, p. 1–7. https://doi.org/10.1109/ICPECTS49113.2020.9336967

[6] Rezeika A, Benda M, Stawicki P, Gembler F, Saboor A, Volosyak I. Brain–computer interface spellers: A Review Brain Sci 2018;8(4):57. PMID: 29601538; PMCID: PMC5924393 https://doi.org/10.3390/brainsci8040057

[7] Farwell LA, Donchin E. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr Clin Neurophysiol 1988;70(6):510–23. https://doi.org/10.1016/0013-4694(88)90149-6

[8] Martínez-Cagigal V, Thielen J, Santamaría-Vázquez E, Pérez-Velasco S, Desain P, Hornero R. Brain-computer interfaces based on code-modulated visual evoked potentials (c-VEP): a literature review. J Neural Eng 2021;18(6). https://doi.org/10.1088/1741-2552/ac38cf

[9] Bin G, Gao X, Wang Y, Hong B, Gao S. Vep-based brain-computer interfaces: time, frequency, and code modulation. IEEE Comput Intell Mag 2009;4(4):22–6. https://doi.org/10.1109/MCI.2009.934562

[10] Nagel S, Spüler M. Asynchronous non-invasive high-speed BCI speller with robust non-control state detection. Sci Rep 2019;9(1):8269. https://doi.org/10.1038/s41598-019-44645-x

[11] Gembler F, Stawicki P, Rezeika A, Saboor A, Benda M, Volosyak I. Effects of monitor refresh rates on c-VEP BCIS. In: Symbiotic interaction: 6th International workshop. Springer Int Publishing; 2017, https://doi.org/10.1007/978-3-319-91593-7

[12] Verbaarschot C, Tump D, Lutu A, et al. A visual brain-computer interface as communication aid for patients with amyotrophic lateral sclerosis. Clin Neurophysiol 2021;132(10):2404–15. https://doi.org/10.1016/j.clinph.2021.07.012

[13] Morimoto T, Kobayashi T, Hirata H, et al. Xr (extended reality: virtual reality, augmented reality, mixed reality) technology in spine medicine: status quo and quo vadis. J Clin Med 2022;11(2):470. https://doi.org/10.3390/jcm11020470

[14] Si-Mohammed H, Petit J, Jeunet C, et al. Towards BCI-based interfaces for augmented reality: feasibility, design and evaluation. IEEE Trans Vis Comput Graph 2020;26(3):1608–21. https://doi.org/10.1109/TVCG.2018.2873737

[15] Arpaia P, Benedetto ED, Donato N, Duraccio L, Moccaldi N. A wearable ssvep BCI for AR-based, real-time monitoring applications. In: 2021 IEEE international symposium on medical measurements and applications. Lausanne, Switzerland; IEEE; 2021, p. 1–6. https://doi.org/10.1109/MeMeA52024.2021.9478593

[16] Bohil CJ, Alicea B, Biocca FA. Virtual reality in neuroscience research and therapy. Nat Rev Neurosci 2011;12(12):752–62. https://doi.org/10.1038/nrn3122

[17] He F, Wu J, Xiao X, Gao R, Yi W, Chen Y, et al. Optimization of stimulus color for SSVEP-based brain-computer interfaces in mixed reality. In Human brain and artificial intelligence, 2023, p. 183–91. https://doi.org/10.1007/978-981-19-8222-4-16

[18] Li Q, Sun M, Song Y, Zhao D, Zhang T, Zhang Z, et al. Mixed reality-based brain computer interface system using an adaptive bandpass filter: application to remote control of mobile manipulator. Biol Signal Process Control 2023;83:104646. https://doi.org/10.1016/j.bspc.2023.104646

[19] Wang S, Wu Y, Li Q. 3D green virtual face p300 spelling paradigm based on mixed reality. In: 2024 4th international conference on bioinformatics and intelligent computing (BIC 2024). Hong Kong; China; ACM; 2024, p. 1–4. https://doi.org/10.1145/3665689.3665711

[20] Käthner I, Kübler A, Halder S. Rapid p300 brain-computer interface communication with a head-mounted display. Front Neurosci 2015;9:207. https://doi.org/10.3389/fnins.2015.00207

[21] Koo B, Lee H, Nam Y, Choi S, Immersive P. BCI with SSVEP in VR head-mounted display. In: 37th annual international conference of the IEEE engineering in medicine and biology society. Milan, Italy; IEEE; 2015, p. 1103–6. https://doi.org/10.1109/EMBC.2015.7318558

[22] Škola F, Liarokapis F. Embodied VR environment facilitates motor imagery brain-computer interface training. Comput Graph 2018;75:59–71. https://doi.org/10.1016/j.cag.2018.05.024

[23] Cho BH, Lee JM, Ku JH, Jang DP, Kim JS, Kim IY, et al. Attention enhancement system using virtual reality and EEG biofeedback. Orlando, FL, USA: IEEE; 2002, p. 156–63. https://doi.org/10.1109/VR.2002.996518

[24] Lécuyer A, Lotte F, Reilly R, Leeb R, Hirose M, Slater M. Brain-computer interfaces, virtual reality, and videogames. Comput 2018;41(10):66–72. https://doi.org/10.1109/MC.2008.410

[25] Coogan CG, He B. Brain-computer interface control in a virtual reality environment and applications for the internet of things. IEEE Access 2018;6:10840–9. https://doi.org/10.1109/ACCESS.2018.2809453

[26] Zhong MG, Pei H, Gao W, Wang X, Y. A new grid stimulus with subtle flicker perception for user-friendly ssvep-based. BCIs J Neural Eng 2023;20(2). https://doi.org/10.1088/1741-2552/acbee0

[27] Hyeyoung H, Youngshin K, Hyosun K, Young-Jun S. Discomfort luminance level of head-mounted displays depending on the adapting luminance. Color Res Appl 2020;45. https://doi.org/10.1002/col.22509

[28] Zehra SR, Mu J, Syiem BV, Burkitt AN, Grayden DB. Evaluation of optimal stimuli for SSVEP-based augmented reality brain-computer interfaces. IEEE Access 2023;11:87305–15. https://doi.org/10.1109/access.2023.3297882

[29] Du Y, Zhao X. Visual stimulus color effect on SSVEP-BCI in augmented reality. Biomed Signal Process Control 2022;78:103906. https://doi.org/10.1016/j.bspc.2022.103906

[30] Krusienski DJ, Sellers EW, Mcfarland DJ, Vaughan TM, Wolpaw JR. Toward enhanced p300 speller performance. J Neurosci Methods 2008;167 (1):15–21. https://doi.org/10.1016/j.jneumeth.2007.07.017

[31] Santamaría-Vázquez E, Martínez-Cagigal V, Marcos-Martínez D, Rodríguez-González V, Pérez-Velasco S, Moreno-Calderón S, et al. Medusa″: a novel python-based software ecosystem to accelerate brain-computer interface and cognitive neu-

roscience research. Comput Methods Programs Biomed 2023;230:107357. https://doi.org/10.1016/j.cmpb.2023.107357
[32] Jurafsky D, Martín J. N-Gram language models. speech and language processing. 2024.
[33] Holmes JK. Spread spectrum systems for GNSS and wireless communication. Artech House, Inc; 2007.
[34] Gembler FW, Benda M, Rezeika A, Stawicki PR, Volosyak I. Asynchronous c-VEP communication tools-efficiency comparison of low-target, multi-target and dictionary-assisted. BCI Spellers Sci Rep 2020;10:1–13. https://doi.org/10.1038/s41598-020-74143-4
[35] Martínez-Cagigal V, Santamaría-Vázquez E, Pérez-Velasco S, Marcos-Martínez D, Moreno-Calderón S, Hornero R. Non-binary M-sequences for more comfortable brain computer interfaces based on C-VEPS. Expert systems applications; vol. 232. 2023. https://doi.org/10.1016/j.eswa.2023.120815
[36] Wolpaw JR, Ramoser H, Mcfarland DJ, Pfurtscheller G. EEG-based communication: improved accuracy by response verification. IEEE Trans Rehabil Eng 1998;6(4):326–33. https://doi.org/10.1109/86.712231
[37] Brooke JB. Sus: a 'quick and dirty' usability scale. In Usability evaluation in industry 1995, p. 189.
[38] Likert R. A technique for the measurement of attitudes. archives of. Psychology 1932;140:1–55.
[39] Gougeh A, Falk R, T. Enhancing motor imagery detection efficacy using multisensory virtual reality priming. Front Neuroergon 2023;6(4):1080200. https://doi.org/10.3389/fnrgo.2023.1080200
[40] Chattha UA, Janjua UI, Anwar F, Madni TM, Cheema MF, Janjua SI. Motion sickness in virtual reality: an empirical evaluation. IEEE Access 2020;8:130486–99. https://doi.org/10.1109/ACCESS.2020.3007076
[41] Krusienski DJ, Sellers EW, Mcfarland DJ, Vaughan TM, Wolpaw JR. Toward enhanced p300 speller performance. J Neurosci Methods 2008;167(1):15–21. https://doi.org/10.1016/j.jneumeth.2007.07.017
[42] Ungerleider LG, Mishkin M. Two cortical visual systems. In: Ingle DJ, Goodale MA, Mansfield R, editors. Analysis of visual behavior. Cambridge (MA); MIT Press; 1982, p. 549–86.
[43] Sauro J. A practical guide to the system usability scale: Background, benchmarks and best practices. 162 2011, Measuring Usability, ISBN 1461062705, 9781461062707
[44] Brandt T, Dieterich M. The dizzy patient: don't forget disorders of the central vestibular system. Nat Rev Neurol 2017;13(6):352–62. https://doi.org/10.1038/nrneurol.2017.58
[45] Riechmann H, Finke A, Ritter H. Using a CVEP-based brain-computer interface to control a virtual agent. IEEE Trans Neural Syst Rehabil Eng 2015;6:692–9. https://doi.org/10.1109/TNSRE.2015.2490621
[46] Grichnik R, Benda M, Volosyak I. A VR-based hybrid BCI using SSVEP and gesture input. In: International work-conference on artificial neural networks. 2019, p. 418–29. https://doi.org/10.1007/978-3-030-20521-8-35
[47] Yao Z, Ma X, Wang Y, Zhang X, Liu M, Pei W, et al. High-speed spelling in virtual reality with sequential hybrid. BCIs IEICE Trans Inform Syst 2018;101(11):2859–62. D. https://doi.org/10.1587/transinf.2018edl8122
[48] Wen D, Fan Y, Hsu SH, Xu J, Zhou Y, Tao J, et al. Combining brain-computer interface and virtual reality for rehabilitation in neurological diseases: a narrative review. Ann Phys Rehabil Med 2021;64(1):101404. https://doi.org/10.1016/j.rehab.2020.03.015
[49] Mcclinton W, Caprio D, Laesker D, Pinto B, Garcia S, Andujar M. P300-based 3D brain painting in virtual reality. In: Extended abstracts of the 2019 CHI conference on human factors in computing systems. 2019, p. 1–6. https://doi.org/10.1145/3290607.3312968
[50] Dehais F, Castillos KC, Ladouce S, Clisson P. Leveraging textured flickers: a leap toward practical, visually comfortable, and high-performance dry EEG code-VEP BCI. J Neural Eng 2024(6):66023. https://doi.org/10.1088/1741-2552/ad8ef7
[51] Spüler M. A high-speed brain-computer interface (BCI) using dry EEG electrodes. PLoS ONE 2017;12(2):172400. https://doi.org/10.1371/journal.pone.0172400
[52] Wen TY, Aris SM. Electroencephalogram (EEG) stress analysis on alpha/beta ratio and theta/beta ratio. Indones J Electr Eng Comput Sci 2020;17(1):175–82. https://doi.org/10.30880/ijie.2020.12.06.020
[53] Nagel S, Spüler M. World's fastest brain-computer interface: combining eeg2code with deep learning. PLoS ONE 2019;14(9):221909. https://doi.org/10.1371/journal.pone.0221909
[54] Castillos KC, et al. Burst c-VEP based BCI: optimizing stimulus design for enhanced classification with minimal calibration data and improved user experience. NeuroImage 2023;284:120446. https://doi.org/10.1016/j.neuroimage.2023.120446