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TOPICAL REVIEW

Virtual Reality Cognitive Gaming Based on Brain Computer Interfacing: A Narrative Review

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ABSTRACT The present article explores the most popular approaches and the best practices for the design and implementation of cognitive gaming interventions that combine Brain Computer Interface (BCI) systems with Virtual Reality (VR). We focus on interventions that target cognitive skills related to perception, visuospatial attention and visuospatial memory. To this purpose, we review the techniques and algorithms that are commonly used for data pre-processing, feature extraction, and classification in such interventions. We discuss issues related to BCI-VR Cognitive Gaming, including the BCI paradigms, the action tasks and environments, user characteristics, algorithms, channels, accuracy, and the most prominent findings. We conclude with a discussion of the current challenges, limitations, future research directions, and the potential commercial applications of BCI-VR in cognitive gaming.

INDEX TERMS Brain computer interface (BCI), cognition, electroencephalography (EEG), gaming, virtual reality (VR).

I. INTRODUCTION

Brain Computer Interface (BCI) is an emerging technology that fuses machine with human thinking by allowing users to communicate with a device solely through their thoughts. In BCI, users generate brain signals that are recognized by a system, which converts them to commands that control a device by thought instead of motor activity. By allowing users to execute actions through their thoughts, BCI establishes a direct communication channel between the brain and the external world [1]. This, makes BCI especially promising for patients with motor impairments.

Indeed, BCI systems have been used successfully in many situations in the past where physical movement was substituted by commands sent from the brain. For example, BCI was used to help people with motor impairments control mobile robots for navigation [2], move prosthetic limbs [3], fly Unmanned Aerial Vehicle control [4], and play video games [5]. Notably, in some cases, BCI has even been successful in inducing brain neuroplasticity, helping patients regain lost motor functions [6].

In recent years, BCI has been combined with Virtual Reality (VR) with promising results [6]. Using graphics, VR simulates real-world conditions that make people more committed to the task, producing thus responses that are stronger and easier to identify by BCI algorithms [7]. This, in turn, improves the BCI outcome. The feedback provided by VR is also richer and more engaging than feedback obtained with traditional means, which is typically in the form of simple 2D stimuli, e.g., a bar on the screen. VR technology may enhance the accuracy of the system, reduce the calibration time, and increase the accuracy of the mental state classification of the user. Virtual environments can also be used as a safe, cost-effective, and flexible training and testing ground for prototypes of BCI applications. For instance, they could be used to train a patient to control a wheelchair with BCI

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and to test various designs for wheelchair control, without any physical risk of operating an actual wheelchair and at a fraction of the cost. Thus, VR can serve as a pre-step to using BCI applications in real-life [6].

BCI-VR systems have been used with success in interventions for various conditions, including stroke [8], [9], spinal cord injury (SCI) [10], Attention Deficit Hyperactivity Disorder (ADHD) [11], Alzheimer's disease (AD), Parkinson's disease (PD) [8], [12], and more. In light of these promising results, our objective here is to review BCI-VR applications, focusing on applications that relate to human cognition. To this purpose, we discuss systems that are based on electroencephalography (EEG), presenting the various brain waves used, the feature extraction techniques, the classification algorithms, the target electrodes, and the classification accuracy results. Specifically, we provide an overview of BCI systems that use EEG control signals based on Motor Imagery (MI), the P300 component, and Steady-State Visual Evoked Potentials (SSVEP) and relate to VR Gaming or the cognitive mechanisms of perception, visuospatial attention and visuospatial memory. Furthermore, we review the objectives, methodology, and findings of BCI-VR studies on gaming systems and discuss the relevant research gaps and challenges that warrant further investigation. This review can further our understanding of the cognitive mechanisms that produce the appropriate EEG patterns for human training, beyond algorithm training.

First, in Section II, an introduction of the main BCI principles is presented, followed in Section III by an analysis of the state-of the-art techniques and algorithms that are most widely used in BCI-VR systems. Then, in Section IV, we review popular EEG-based BCI applications related to cognition. In Section V, we summarize the various challenges and discuss future directions related to BCI and VR. In the final section, we provide our concluding remarks and limitations on the topic.

II. BCI PRINCIPLES

A typical BCI system is composed of six basic processing components as shown in Figure 1: (1) raw EEG signal acquisition, (2) pre-processing of EEG signal for background noise cleaning, (3) extraction of specific application features from the clean data and selection of more discriminative features, (4) classification of the selected features, (5) decision making linked with device and command, and (6) application execution and feedback to the user. These processing components are present in all categories of BCI systems, namely, Active, Reactive, and Passive systems.

A. CATEGORIES OF BCI TECHNOLOGIES

BCI systems analyze the electrical brain activity that is recorded through non-invasive methods by electrodes placed on the scalp. Signals are amplified and digitized by preprocessing strategies and the relevant signal features are extracted, processed, and translated into commands that can control external devices or applications. There are 3

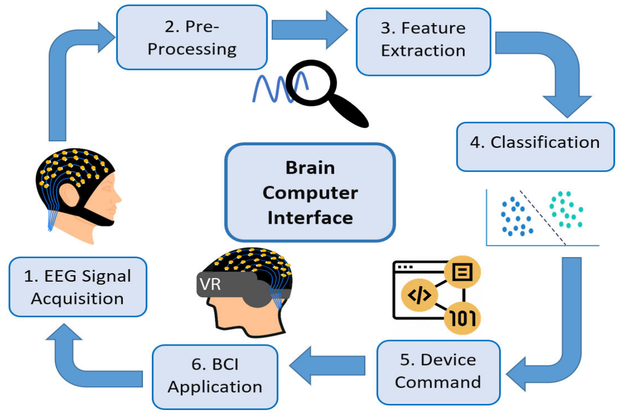

FIGURE 1. Main components of a BCI-VR Gaming system.

TABLE 1. Categories of BCI systems.

BCI Category	Description
Active	Controlled by the user through the execution of a mental task [15].
Reactive	Brain activity is modulated in reaction to an external stimulus provided by the BCI system [16].
Passive	Monitors brain activity without requiring the user to perform any mental task or to achieve a certain goal [21].

categories of BCI systems. In active BCI, the user performs a mental task that produces a specific pattern of EEG activity, which the BCI system detects. The most common paradigm used is motor imagery where participants have to imagine moving parts of their body, without actually performing the movement. In a reactive BCI, brain activity is modulated in response to an external stimulus given by the BCI system. The most commonly used paradigm is the P300 speller where stimuli, such as letters or symbols, are flashed sequentially on a screen and participants direct their attention to the symbol they want to select. Passive BCI simply monitors the EEG activity of the users, without requiring them to perform any mental tasks. The EEG activity monitored by passive systems is not intentionally modulated to achieve a specific goal but to extract a conclusion such as the user's emotional state [21] (TABLE 1).

B. FURTHER CATEGORIZATION OF BCI TECHNOLOGIES

Depending on the recording method, BCI can be categorized into invasive or non-invasive. Invasive BCI requires implanting microelectrode arrays to the brain to record the activity of neurons directly. In contrast, non-invasive BCI, records electrical activity with electrodes placed on the scalp. Non-invasive BCI, is used more often to detect a variety of control signals, including Slow Cortical Potentials (SCP), Steady-State Evoked Potentials (SSEP), Motor Imagery (MI), Error Potentials (ErrP), and the P300 Evoked-Related Potential (ERP). In the BCI-VR, the most common control signals are the P300, the MI, and the SSVEP [4].

TABLE 2. EEG frequency bands [24].

Band	Frequency (Hz)	Activity
Delta	0.5 - 4 Hz	Deep sleep, no focus, unconscious.
Theta	4 - 8 Hz	Deep relaxation, internal focus, meditation, intuition access to the unconscious. Material such as imaging, fantasy, dreaming.
Low Alpha	8 - 10 Hz	Wakeful relaxation, consciousness, awareness without attention or concentration, good mood, calmness.
High Alpha	10 - 12 Hz	Increased self-awareness and focus, learning of new information.
Low Beta	12 - 18 Hz	Active thinking, active attention, focus towards problem solving, judgment and decision making.
High Beta	18 - 30 Hz	Engagement in mental activity, alertness and agitation.
Low Gamma	30 - 50 Hz	Cognitive processing, senses, intelligence, compassion, self-control.
High Gamma	50 – 70 Hz	Cognitive tasks: memory, hearing, reading and speaking.

TABLE 3. Summary of features of different neural mechanisms.

EEG Paradigm	MI	P300	SSVEP
Nature	ERD/ERS	ERPs	SSEP
Advantages	Doesen't require any external stimulation. Free will operation	Almost no training needed	Almost no training needed
Disadvantages	Requires training	Requires external stimulation. Could provoke tiredness in users.	Requires external stimulation. Could provoke tiredness in users.
Accuracy	65 -70%	6X6 symbol matrix 90%	90%
Training Time	10-30 mins	5 mins	5 mins

BCI systems can also be categorized as dependent or independent. Dependent systems are those that require some form of motor control by the user. MI-based BCI is a good example of a dependent BCI system that has been used extensively. In contrast, independent systems don't need any form of motor control and are, therefore, ideal to use with stroke patients and other patients with motor deficits. For example, an SSVEP-based independent BCI system allows the user to produce binary responses (e.g., yes vs. no) without any motor response [22].

Finally, a BCI system can be either synchronous or asynchronous. In synchronous BCI, the user is prompted by the system to perform an interaction within a certain time span. Conversely, in the case of asynchronous BCI, the user interacts with the system by sending commands throughout the session, without any prompts. Although synchronous systems can be designed more easily, they are not as user-friendly as asynchronous systems [23].

C. EEG ACQUISITION AND FREQUENCY BANDS

Electrode placement on the scalp is guided by background knowledge on the functions of the four lobes of the cerebral cortex. Most commonly, electrode placement is performed according to the international 10-20 system [24] that labels electrodes based on positions over the frontal, parietal, temporal, and occipital lobes, indicated by the letters F, P, T, and O respectively. Each electrode is also assigned a number, resulting in a unique combination of letter and number. Electrodes with odd numbers are placed to positions on the left side of the scalp and electrodes with even numbers to positions on the right side. Positions in the midline are indicated by z (zero).

EEG records the electrical brain activity produced from the different structures of the brain by measuring voltage fluctuations coming from the ionic flows into the brain neurons. EEG signals are divided into specific ranges that are more prominent in certain states of the brain. EEG frequency bands are associated with specific brain activity as depicted in TABLE 2 [24].

D. EEG CONTROL SIGNAL PARADIGMS

The most widely used EEG-based BCI-VR systems are classified into four basic paradigms according to the procedure with which the brain activity is extracted. These are: (a) Motor Imagery (MI), (b) Positive 300 (P300), (c) Steady-State Visual Evoked Potentials (SSVEP) and (d) Hybrid signals (see also TABLE 3).

1) MOTOR IMAGERY (MI)

In the MI paradigm the user sends a command to an external device by imagining moving a limb without performing any physical activity. This is made possible by detecting EEG activity in the somatosensory motor cortex and generating discriminant patterns in the brain signals. The most detectable activities in the somatosensory motor cortex that are distinguishable in the EEG signal correspond to the left vs. right hand movement, foot movement, and tongue movement [25]. Both the physical and the imagined limb movement generate a unique pattern in the alpha and beta bands, more specifically in the "mu" and "SMR" signals [9], [26]. SMR signals are encapsulated in the alpha (mu) (9 - 11 Hz), beta (13 - 30 Hz), and gamma (> 30 Hz) frequency bands [8], [9]. These patterns are reflected with a power decrease termed "event-related desynchronization" (ERD) that correlates with the preparation of movement [13], or with a power increase

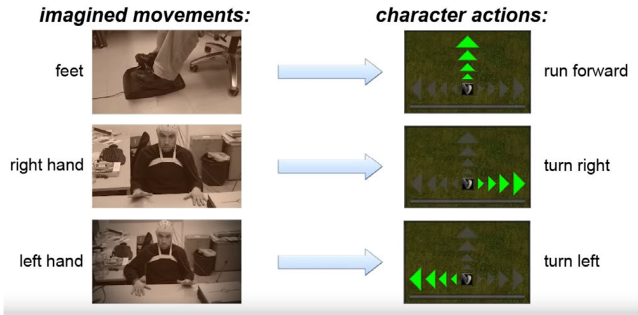

FIGURE 2. An example of an mi-based bci system. The left column presents the imagined movements that the users must recall to send a command to the game, to move the avatar in the direction of their choice as shown in the right column.

termed "event-related synchronization" (ERS) that indexes a resting state [27]. Notably, research has shown that MI generates the same pattern in the motor cortex during the execution and the imagination of the movement [28]. ERD / ERS models are localized because of the somatotopic arrangement that exists in the motor cortex. For example, the representation in the upper limb area is on the mantle of the motor cortex, and followed by lateralization [16], which makes the spatial discrimination easy among left-hand and right-hand EEG patterns.

The most important electrodes that can detect distinct patterns in the somatosensory motor cortex are C3, C4 and Cz. In the upper limbs, there is an evident contralateral dominance for left-right limb recognition [17], [18]. The presence of contralateral and ipsilateral variations in mu activity are used as distinct signatures in BCI to discriminate left and right hand movement (see Figure 2) [29]. In contrast, left and right foot MI discrimination does not rapidly evolve because the locations of the areas of the somatosensory cortex that correspond to the left and right foot are very close to each other. Furthermore, the foot motor area is located deep in the sensorimotor cortex, making it difficult to differentiate the nearly identical EEG activity from the left and the right foot [16]. Therefore, although studies have used MI-based BCI using feet, they generally did so without discriminating across the left and right sides [30], [31] (see also Figure 2).

2) POSITIVE 300 (P300)

The visual P300 is one of the most popular examples of EEG-based BCI systems, especially in the most modern implementations of BCI-VR gaming. BCI systems with P300 are based on sequential flashing stimuli, such as symbols, letters, or objects. In 1988, Farwell and Donchin pioneered the use of the visual P300-BCI [32] creating what is today known as the P300 Speller. The P300 is obtained by analyzing event-related potentials (ERP). An ERP is generated by averaging the EEG signal, locked to a particular event such as a visual stimulus presented on a screen. The P300, in particular, is produced as a response to infrequently presented stimuli that are recognized by the user. It's a positive peak in the EEG ranging from 5 to 10 microvolts in size that appears

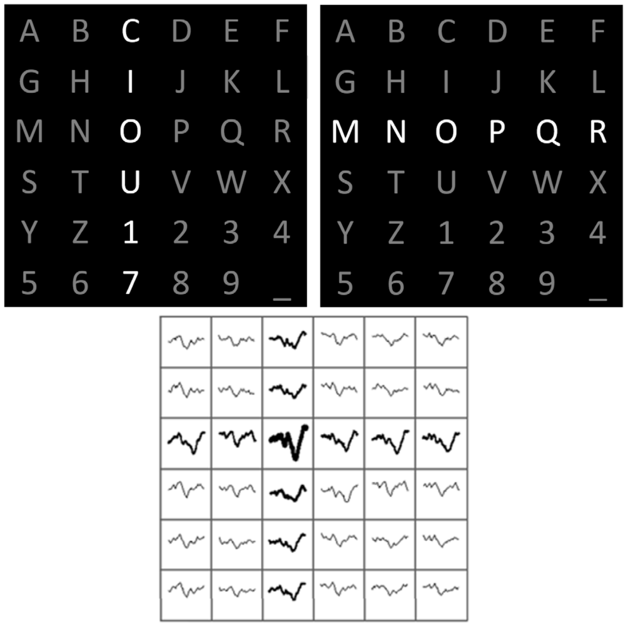

FIGURE 3. An example of a 6 × 6 symbol p300 matrix-based bci system. The user "writes" the letter "o" by focusing on the letter. The system recognizes the correct letter because of the positive peak generated in the eeg signal 300ms after the flash [34].

about 300ms after the onset of the event [34] (see Figure. 3). The most common locations of the recording electrodes for measuring the P300 are in midline electrodes Pz, Cz, and Fz. The most important advantage for using P300-based BCI systems is that most users can generate the P300 with high accuracy and with almost no training. Therefore, the participant can rapidly and easily use the system to handle an application. The disadvantage of P300-based BCI systems is that the tasks they rely on are attentionally demanding and thus elicit fatigue to the users [34]. In addition, given the visual nature of the tasks, users with vision impairments often have difficulties using the system and produce rather poor results [35].

3) STEADY-STATE VISUAL EVOKED POTENTIALS (SSVEP)

The SSVEP is another popular visual paradigm in BCI [36]. In SSVEP, users direct their gaze to flickering stimulations, a task that requires good attention control as shown in Figure. 4. The most important locations for the recording electrodes are in the occipital lobe and particularly locations O1, O2, and Oz. Focusing on the flickering stimulus generates an EEG pattern whose frequency correlates with that of the stimulus. To produce the stimulus, light-emitting diodes (LED) are often used. Typically, multiple flickering stimuli with distinct flickering frequencies that represent different commands are presented to the user. The stimulus that matches the pattern of EEG activity is then selected and the command associated with it is executed. The SSVEP has many advantages. One notable advantage is that because the stimuli are exogenous, it can be used without user training. Stimuli can flash at many different frequencies, allowing

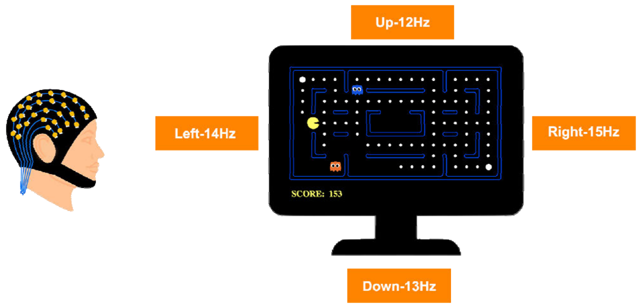

FIGURE 4. SSVEP PARADIGM: The user moves the game character by focusing on the corresponding flickering lights. By focusing on the left flickering light, the eeg signal reflects the 14Hz stimuli and the system triggers a movement to the left [37].

the user to give different commands to the external device. In addition, the SSVEP frequencies can be more reliably classified than the ERP. However, as with the P300, this paradigm causes fatigue to users, especially when using stimuli with low flickering frequencies [37]. This paradigm is also not suitable for the visually impaired as it entails gaze movement. That said, Min et al. [38] have recently proposed a new SSVEP paradigm that uses a grid-shaped line array that is gaze-independent.

Finally, it should be noted that, along with the SSVEP, a number of similar approaches can be found in the Steady State Evoked Potential (SSEP) family: steady-state somatosensory evoked potentials (SSSEP), steady-state auditory evoked potentials (SSAEP) [39], and hybrid SSSEP-P300 applications [40].

III. BCI TECHNIQUES AND ALGORITHMS

A. PRE-PROCESSING STRATEGIES

One of the biggest challenges in EEG-based BCI applications is that background noise must be eliminated before performing the analysis. Noise can be caused by both exogenous and endogenous factors. Exogenous factors include televisions, mobile phones, computers, lighting fixtures, etc. Endogenous factors include movement, respiration, skin resistance fluctuations, or other bioelectrical potentials, such as electromyographic (EMG) activity, electrocardiographic (ECG) activity, electrooculographic (EOG) activity, etc. [41]. Therefore, one needs to clean the raw EEG to better suit the requirements. To achieve this, a variety of pre-processing methods can be applied [42], [43], [44], [45], [46], including:

- Notch filtering at 50 or 60Hz (depending on geographic location) to remove power line noise.
- High pass filtering with a low cut-off frequency to erase the drift of the baseline.
- Band pass filtering to pick the appropriate bands.
- Epoching the continuous data to extract segments, time-locked to an event, in specific time-windows.
- EEG amplitude clipping to force the EEG signal into a specific range.
- Removing bad trial samples from the EEG.
- Normalizing the data to zero mean and unit variance using z-scores in order to accelerate convergence and avoid getting stuck in local minimums.
- Down-sampling to accelerate the calculations and reduce memory.
- Selecting key electrode positions according to the goal of the application.
- Rejecting artifacts using thresholding techniques such as Principal Component Analysis (PCA) or Independent Component Analysis (ICA).

B. FEATURE EXTRACTION

After the pre-processing that cleans up the signal, the most important features in the EEG signal must be extracted. The most commonly used EEG feature types in BCI systems are: statistical, manually-selected, and data-driven adaptive features [47]. The selection of a toolset for dealing with features is a very critical process because of the high complexity and dynamical structure of the EEG signal [48]. There are various ways to achieve feature extraction in the time domain, frequency domain, time-frequency domain, and spatial domain. Extracting features that depend on temporal information only, results in rejecting spectral information. On the other hand, extracting features in the frequency domain only, results in rejecting temporal information.

Two effective techniques for feature extraction are the Discrete Wavelet Transform (DWT) and the Wavelet Packet Decomposition (WPD). These methods can decompose the EEG signals at multiresolution and multiscale, which is useful as important information in the EEG signal is conveyed in different frequency bands. Moreover, they can extract dynamic features, which is very important given the non-stationary and non-linear nature of the features [49], [50].

Furthermore, time-frequency based methods are highly beneficial when analyzing EEG signals, as they are extremely dynamic. Spatial domain methods and frequency domain methods can be blended to extract more distinct features leading to increased classification accuracy. For better feature extraction, the selection of the most efficient electrode positions, is very important. This can be achieved by setting weights using spatial domain methods [46], [51]. Commonly, high-dimensional features are extracted from the EEG signal. Because of this, statistical transformation methods like Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are used for feature selection and dimensionality reduction. However, these methods are computationally expensive and can reduce classification accuracy [46], [52].

To address the problem of high dimensionality, Evolutionary Algorithm (EA) optimization techniques for feature selection from large feature sets are used [53]. Using filter bank approaches, such as the Common Spatial Pattern (CSP), has had a major impact on feature treatment in EEG data [54] and is considered to be one of the most powerful feature extraction techniques widely used in BCI [55]. This method uses a spatial filter that changes the brain signals in a single space where the variation of a feature set is maximized, while lower variation is observed in the rest of the feature set. The CSP approach may not accomplish adequate performance because of the optimal frequency band for each individual. Therefore, selecting an optimized filter band can improve performance. However, selecting the optimal sub-band through pure CSP may take much time [56]. Also, the CSP algorithm has many different variants that are characterized by enhanced performance in BCI systems such as the Adaptive Composite Common Spatial Pattern (ACCSP) and the Self Adaptive Common Spatial Pattern (SACSP) algorithms [1].

Feature extraction methods that are based on Neural Networks (NN) utilize a framework that combines all three phases of feature extraction, selection and classification in a single pipeline. Despite the long training phase in NN, new invisible data can be analyzed as soon as the network parameters are defined [57]. This results in more effective computations, which in turn extract better features leading to higher classification accuracy.

Finally, it is worth noting that although many researchers skip the feature selection phase, systems using the selection phase seem to achieve greater accuracy [24].

C. FEATURE CLASSIFICATION

Several algorithms are used to classify features. We have identified the following as the most common:

1) CONVENTIONAL MACHINE LEARNING

The k-Nearest Neighbors (k-NN) algorithm is a well-known non-parametric classification method. In k-NN, the input data corresponding to the different classes create unique groups in the feature space. Adjacent groups are classified together and are defined as neighbors. A distance metric is then used as a measure of similarity of feature vector test among the features of all the classes [57]. The main factors governing the k-NN algorithm are the set of neighbors and the type of distance measurements. k-NN algorithms are not so widespread in the community of BCI because they are very sensitive to the dimensionality of the feature vector [58]. However, when used in low-dimensional feature vectors systems, k-NN can be of great value. Notably, k-NN generates strong outcomes when blended with effective feature selection or feature reduction algorithms.

The Linear Discriminant Analysis (LDA) is another approach that relies on finding the linear patterns of feature vectors that express the corresponding features of the signal. The LDA algorithm separates the classes representing different objects by using hyperplanes. The isolating hyperplane is achieved by searching for the projection that maximizes the distance among the means of the classes and minimizes the interclass variance [59]. The LDA has very low computational requirements and is therefore commonly used. Indeed, it has been applied successfully in many BCI systems that rely on MI, P300, and either multiclass or asynchronous BCI. Nevertheless, while providing good results because of its immunity to non-static issues, due to its extremely linear nature, it downgrades performance in cases of too much non-linear data [60].

Finally, another approach that can be used is the Support-Vector Machine (SVM). The SVM classification algorithm is a machine learning classification algorithm based on statistical learning theory. The SVM improves generalization, minimizes experience risk and confidence range, solving the problems of overlearning, model selection, dimensionality reduction and nonlinearity in algorithm of pattern recognition under small sample conditions. The algorithm estimates the optimal classification plane that maximizes the classification interval between the two classes [61].

The SVM is a classifier that creates a set of hyperplanes for separating the feature vectors in several classes. SVM picks the hyperplanes that maximize the margins, that is, the distance among the hyperplanes and the nearest training samples [62]. In general, the SVM has been widely accepted by the researchers as one of the simplest algorithms used in the area of BCI. It also proves to be robust with high-dimensional datasets, which means even with high-dimensional feature vectors, a large set of training data is not necessary for a high outcome [63]. Notably, there is no tradeoff with regards to execution speed in real-time BCI integrations.

2) DEEP LEARNING

Deep learning methodologies are increasingly popular in BCI due to their ability to process and analyze complicated patterns in brain signals. In particular, deep learning greatly simplifies the processing of EEG signals as the multiple layers in the network represent and solve a smaller problem, helping the decision-making phase to solve the wider problem by using pre-processing techniques, feature representations, etc. [52]. In addition, there seems to be great success in representing complex patterns with the development of deep learning.

Deep learning algorithms learn hierarchical representations of input data with non-linear transformations techniques [46], [52]. In deep learning, the stacked layers insert a linear transformation to the network and then trigger it through the activation function. The variables of the stacked layers are learned by default with the help of an objective function. Different deep learning architectures have been used, including convolutional neural networks, recurrent neural networks, and more.

As their name implies, Convolutional Neural Networks (CNN) operate using a linear function called convolution. CNN are widely used for image, video, and EEG analysis. The CNN contain an input layer, where learning data are fed, several hidden layers that process and analyze the input data to create a trained model, and an output layer that predicts the answer to a problem. In the process of network learning, the higher-level features are simplified to lower-level features [46], [83]. The convolution is completed by convolving the signals with multiple 2D filters in order to extract useful complementary features. The connecting weights are changed during the training process in order to reduce the classification error [84]. Excessive increase in network levels dramatically increases the ability of the neural network to generalize, resulting in overfitting and recognition only in the data it has been trained with. Nevertheless, there are multiple techniques for tackling the problem of overfitting. An effective technique is to use a pooling layer that works as a down-sampling strategy that applies various types of pooling such as max, sum, and average. Pooling layers and convolution layers can decrease the complexity and the feature maps sizes [46].

Recurrent neural networks (RNNs) include embedded memory cells that store previous network states for later use. The output of these networks results from both the current input and the previous output, and that is why they are referred to as recurrent. By nature, this type of networks is suitable for solving time series related problems such as EEG signal analyses. The memory cells included in the network contain input, output, and forget ports, to determine the output of the cell. The most widely used types of RNNs are the Short-Term Networks (LSTM), the Gated Recurrent Units (GRU), and the peephole connection LSTM. By their very nature, these networks have the ability to remember and process complex previous values over a long period of time by subdividing the trials into multiple parts and by extracting temporal-related features as opposed to CNN that process individual trial items to extract spatial features [46].

Finally, the Boltzmann Limited Machine (RBM) is sometimes used for feature classification. It is a multiplicative unsupervised learning model that contains an input layer, a hidden layer, and two-way connections among the two layers. Each node of the input layer is connected to all the other nodes in the hidden layer. The input data are composed of latent features that are used to reconstruct the data from the input in a backward procedure to create new data points in the hidden layer and vice versa [24], [46], [91]. A Deep Belief Network (DBN) is the total of various layers of RBM. During the learning procedure, the 1st layer in the DBN is the visible and the 2nd layer is the hidden layer. Then, the 2nd layer becomes the visible layer and the 3rd layer the hidden one. The procedure continues in the same pattern until all layers in the network are learned [46].

IV. BCI VIRTUAL REALITY AND COGNITIVE TASKS

A. METHODOLOGY

The review was conducted in 5 phases based on Bargas-Avila and Hornbaek and the Cochrane methodology [120], [121], [122].

1) PHASE 1: EVALUATION OF PUBLICATIONS

We searched 9 electronic databases, covering a balanced range of disciplines, such as computer science, computer engineering, neuroscience, medical research and multidisciplinary sources. The databases included in the review were: 1. ACM Digital Library (ACM), 2. Google Scholar, 3. IEEE Xplore (IEEE), 4. MEDLINE, 5. PubMed, 6. Sage, 7. ScienceDirect (SD), 8. Scopus, 9. Web of Science. We limited the search to a period of ten years (March 2011 to March 2021).

Search terms: We applied three queries to each database since we aimed to study the ‘‘BCI-VR Gaming technology with Cognitive tasks’’:

A. BCI-VR Gaming
B. BCI AND Cognitive tasks
C. BCI-VR Gaming AND Cognitive tasks

Search procedure: The search term was used to retrieve the publication titles, abstracts, and keywords.

Search results: The search results and analysis are summarized in Fig. 5.

2) PHASE 2: PUBLICATIONS RETRIEVED FOR DETAILED EVALUATION

First exclusion: We removed 368 entries because they did not fit within the timeframe we set. As a result, 1419 articles remained.

Second exclusion: Duplicate studies in the databases (e.g., various terms producing similar result into the same database) and among databases (e.g., different databases producing similar result) were excluded. We excluded 278 duplicate studies. This narrowed down our findings to 1144 different articles.

Third exclusion: We limited the publications to the documents written in English. We excluded articles that we didn't have access to and articles that were not official articles but referred instead to oral presentations, posters, magazines and in general grey literature without official review. Therefore, we removed 601 articles. The 540 articles that remained include journal articles, conference papers, and book chapters.

3) PHASE 3: PUBLICATIONS INCLUDED IN THE ANALYSIS

Final exclusion: Since the purpose of this review is to investigate the use of BCI-VR Gaming in relation to the cognitive mechanisms of perception, visuospatial attention and visuospatial memory, we removed publications that focused on other topics. We also excluded all studies that used invasive or semi-invasive techniques, as well as studies in which BCI was not based on EEG. We excluded also studies that used approaches other than Motor Imagery (MI), P300, and Steady-State Visual Evoked Potentials (SSVEP). Finally, we excluded studies that did not mention the methodology or the algorithms they used for pre-processing, feature extraction, classification, and performance, or for which the findings were not clear. Based on these criteria, we removed 513 publications. As a result, we concluded with 27 articles (17 studies of BCI-VR Gaming, 8 studies of BCI with Cognitive tasks, and 2 studies that involved both BCI-VR Gaming and cognitive tasks), as presented in Fig. 5.

4) PHASE 4: DATA GATHERING

In this phase, we extracted all the important information from all the publications to analyze them. We recorded the

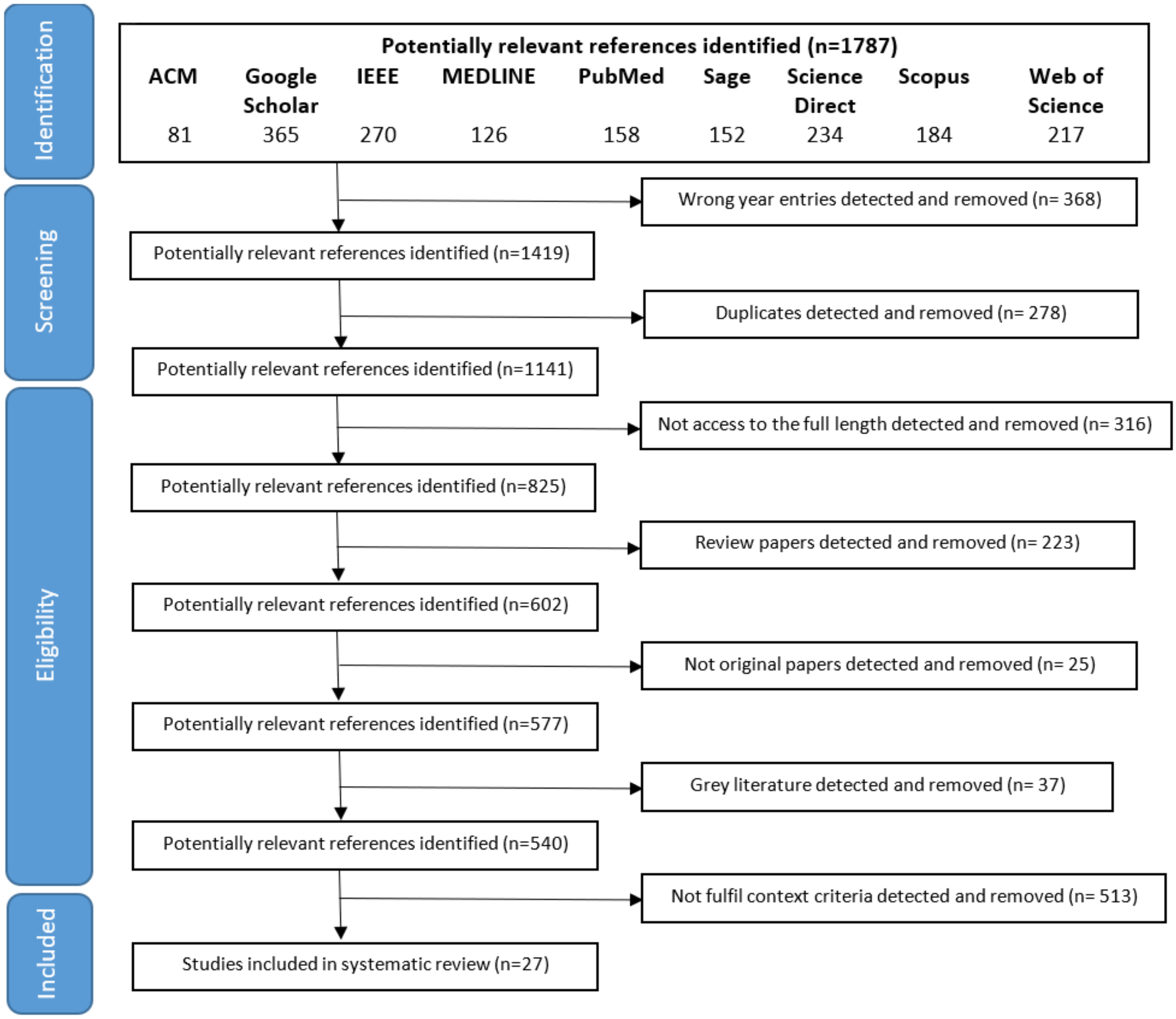

FIGURE 5. Summary of search results and analysis for the identification and selection of related studies.

following information from all the studies: the BCI paradigm, VR action scene, number of participants, feature extraction algorithm, classification algorithm, EEG electrodes used, and key findings.

5) PHASE 5: DATA ANALYSIS

We used thematic analysis to classify the selected articles based on the following characteristics: the BCI paradigms, the BCI pre-processing strategies, feature extraction algorithms, classification algorithms, the BCI-VR challenges, and the BCI-VR gaming future directions.

B. BCI-VR GAMING

Research on BCI-VR Gaming systems has attracted significant interest for both healthy people and people with motor impairments. VR is a computer technology that uses computer graphics to simulate real environments. Instead of viewing a screen, users are immersed in realistic 3D virtual environments and can interact with the objects as if they were real [64]. This can result in diminished training time and increased efficiency. Also, VR technology makes the training interesting and engaging for the user. Applied in rehabilitation medicine, VR has had documented success, when used for stroke patients with hemiplegia after rehabilitation training [65], Parkinson's Disease (PD) rehabilitation [66], upper-limb prosthetics [3], and wheelchair control [67].

The most widely used methods by researchers for BCI-VR Gaming are MI, P300, and SSVEP. TABLE 4 summarizes the most significant BCI-VR games from March 2011 to March 2021.

In one of the studies we reviewed, Xu et al. [68] developed a simulation of a robotic arm in a VR game designed to compare the performance of low-cost devices (OpenBCI) to medical grade BCIs (Neuroscan). The virtual robotic arm was operated using the MI technique and the findings showed that low cost BCIs can produce really good outcomes. The best result of classification accuracy of the robotic arm control was 76.3% with the low-cost device and 79% with the medical quality device [68].

In another study, Vourvopoulos et al. [69] developed the Neu-Row, a novel BCI system that provides multimodal vibrotactile feedback in the VR experience with the use of head-mounted display (HMD) to achieve more distinct activations in the motor cortex areas. The NeuRow system is a holistic BCI approach combining MI, immersive VR environments, and sensory stimulation. During the experimental training, the virtual hands were controlled using only the MI-BCI paradigm in the system. Healthy users were asked to perform a rowing motion with virtual hands using MI. To enhance realism, vibration and tactile feedback were provided. Results showed that the average left-right hand movement accuracy was 70.7%.

In a follow-up study, Vourvopoulos et al. [70] used NeuRow with a 60-year-old patient with left hemiparesis caused by a stroke in the right temporal lobe 10 months before. The patient imagined moving his left and right hands to paddle a boat in a virtual environment across 10 sessions carried out over a period of 3 weeks. Electrophysiological data showed increased brain activation, similar to that of healthy individuals. Results showed an improvement in motor function as a result of VR feedback and MI training. This result was also documented in imaging data collected. Overall, the findings of this study extend previous research by showing neuroplastic changes in specific targeted areas of the brain and the effectiveness of BCIs using MI for motor rehabilitation. They also suggest that the systematic training with similar systems that control applications through imagined movement can improve the physical motor ability of individual patients with motor impairments.

To explore if P300-BCI VR headsets can achieve similar classification accuracy as 2D monitors, Käthner et al. [71] conducted an experiment in which 18 participants used three different display methods to perform a typical task with a BCI speller. The first display was a 5 X 5 matrix turning the BCI speller into a typical wide screen. The second was an identical 5 X 5 display that was however viewed in immersive VR. The third display was the same as the second one with the exception that only a single letter at a time appeared in the 5 X 5 BCI speller. Results revealed similar spelling accuracy across the three display conditions (96%, 96%, and 94%, respectively), suggesting that VR headsets can accomplish similar accuracy as 2D monitors and that fast P300-BCI communication can be achieved in VR experiences.

In another study, Zeng et al. [72] developed an interface between the brain and a lower robotic limb using the SSVEP paradigm in a virtual environment to help people with ankle movement problems to perform robotic-based rehabilitation tasks. The lowest limb control accuracy was 80% and the highest 100%, documenting the effectiveness of this approach.

In an earlier study, Zhang et al. [65] presented a BCI-based lower-limb rehabilitation training system that merged BCI, VR, and robotics. In the system, a robot and an avatar performed similar movements at the same time while the user could perform various commands such as rotation to the left and to the right, forward movement, etc. Results showed an 85.6% classification accuracy for three participants.

C. BCI FOR ATTENTION, MEMORY AND VISUOSPATIAL SKILLS

BCI neurofeedback training involves stimulating brain areas with repetitive reward and feedback training, e.g., when the user tries to move a robotic arm through mental imaging strategies [78], [79], [80]. TABLE 5 presents EEG-based BCI studies targeting the cognitive mechanisms of perception, visuospatial attention and visuospatial memory.

In [81], a BCI neurofeedback game based on MI paradigm was developed to help children with ADHD. The band power results showed that the children improved their attention while playing the game. At the same time, they had fun and were generally in a relaxed state. This is aligned with the result of other studies showing that new approaches that use either 2D or 3D games in combination with BCIs, can implement effective interventions for patients with ADHD, mainly by employing mindfulness training. Techniques such as mindfulness training facilitate brain maturation, improve visual processing, and enhance cognitive skills, by increasing the ability to retain the attention of the user for extensive period of time [82], [83], [84].

In an example study, Qian et al. [83] showed that a BCI intervention can significantly reduce inattention after 8 weeks of training. Notably, inattention was reduced more in an ADHD intervention group than a control group that included participants without attention difficulties [83]. Of course, additional research may be needed to assess the effects on ADHD patients who have been treated with BCI for extended periods of time, and to develop adaptive systems that can profile and use the users' characteristics to adapt the system [82].

Promsorn et al., [89] measured EEG activity while participants performed a spatial ability task. Electrical activity was processed offline and the following frequency bands were analysed: delta (0 - 3 Hz), theta (4 - 7 Hz), alpha (8 - 12 Hz), beta (13 - 30 Hz) and gamma (31 - 47 Hz). The alpha, beta and gamma frequency bands of the participants increased significantly during the execution of the spatial task compared to baseline. BCI studies on video game applications have shown that BCI can offer many advantages when combined with cognitive and gamification techniques. The influence of neurofeedback in classic video games based on BCI is very promising for enhancing the level of attention and cognitive function in both healthy and motor-impaired users [84]. EEG video game control is better suited for BCI because of the portability, affordability, safety, high temporal resolution, and non-invasive access it provides to users with motor impairments, in contrast to other BCI applications such

TABLE 4. Summary of EEG-based BCI-VR gaming studies.

Author	BCI paradigm	VR action task	No. of subj.	Feature extraction	Classification algorithm	Channels	Accuracy
J. Xu et al. (2020) [68]	MI	Simulation of robotic virtual arm	2	FBCSP	SVM	2 channels: (C3, C4) “mu” and “beta” waves	76.2%
Vourvopoulos et al. (2016) [69]	MI	Virtual rowing with hand movements	13	CSP	LDA	8 channels: (FC5, FC6, C1, C2, C3, C4, CP5, CP6)	70.7%
Vourvopoulos et al. (2019) [70]	MI	Virtual rowing with hand movements	1	CSP	LDA	8 channels: (FC5, FC6, C1, C2, C3, C4, CP5, CP6)	60%
A. Kreilinger et al. (2016) [73]	MI	Car game	10	DP	LDA	32 channels: Important Used: (C3, Cz, C4)	70%
Achanccaray et al. (2017) [10]	MI	Virtual hand control	8	CSP, Log trans.	Adaptive neurofuzzy inference system	16-channels (AF3, AF4, FC3, FCz, FC4, C3, Cz, C4, T7, T8, CP3, CPz, CP4, Pz, PO3, PO4) References: (FZ, A1)	89%
Lupu et al. (2018) [75]	MI	Limb movement control	3	CSP	LDA	12-channels: (FC1, FC2, FC5, FC6, C3, C4, C5, C6, CP1, CP2, CP5, CP6)	85%
Vourvopoulos et al. (2015) [75]	MI	Virtual left and right hand control	9	CSP	LDA	8 channels: (FC3, FC4, C3, C4, C5, C6, CP3, CP4)	65.6%
Munoz et al.(2014) [113]	MI	Virtual left and right hand control	8	CSP	LDA, SVM	8 channels: (F3, F4, FC5, FC6, AF3, AF4, F7 andF8)	96.7%
Badia et al. (2013) [113]	MI	Controlling a virtual arm	9	N/A	2 dimensional linear classifier	(FC3-FC4 and CP3-CP4). Ground: FPz Reference: A2	85%
Zheng et al. (2013) [114]	MI	Virtual navigation	1	CSP	LDA	5 electrodes placed around the sensorimotor cortex area	67.5%
Amaral et al. (2017) [76]	P300	Virtual objects flickering	17	Max-SNR	I Bayesian	8 channels: (C3, Cz, C4, CPz, P3, Pz, p4, POz)	80%
Tidoni et al. (2017) [77]	P300	Virtual character control	21	N/A	LDA	8 channels: (Fz, Cz, P3, Pz, P4, PO7, Oz, PO8)	89%
Käthner et al.(2015) [71]	P300	Spelling in virtual scene	18	N/A	Stepwise linear discriminant analysis (SWLDA)	8 channels: (Fz, Cz, P3, P4, Po7, POz, PO8, Oz)	80.5%
Tarnanas et al. (2012) [115]	P300	Virtual navigation in a museum	50	N/A	kNN	N/A	87%
Zeng et al. (2017) [72]	SSVEP	Whack a Mole	5	FFT	N/A	41 channels	90%
Zhang et al. (2015)[65]	SSVEP	Virtual character control	3	N/A	Canonical correlation analysis (CCA)	3 channels: (Oz, O1, O2)	85.6%
Legeny (2011) [116]	SSVEP	Virtual navigation	1	N/A	LDA	3 channels: (Cpz, POz, O1, Oz, O2, and Iz)	91%

CSP: Common Spatial Pattern, SVM: Support Vector Machine, LDA: Linear Discriminant Analysis, DP: Discriminant Power, FFT: Fast Fourier Transform, SNR: Ratio of Signal power and Noise power.

as environmental control, cursor control, robotic arm control, wheelchair control, etc. [85]. BCI neurofeedback gaming has been shown to improve the level of attention and, memory, of the users [81].

Mental training and concentration seem to also benefit visuospatial memory and perception in many professional areas, like medical surgery, sports, and music. Thus, BCI applications may help people improve their cognitive skills by using EEG patterns and visualization methods to restore movement and communication [87], [88]. Hammer et al., (2012) [106] conducted an experiment where participants underwent a psychological test-battery before performing an MI task. The psychological test-battery included performance tests, personality tests, clinical tests, and the vividness of movement imagery questionnaire. In the BCI-MI session, participants were instructed to imagine the movement of the left hand, the right hand, and the right foot. Results showed that system recognition accuracy across the three imaginary movements was 74%. In another study carried out by Promsorn et al. [89] participants performed a spatial

TABLE 5. Summary of eeg-based bci with cognitive tasks.

Author	BCI paradigm	Action	No. of subj.	Feature Extract.	Classification algorithm	Channels	Key Findings / Accuracy
BCI-based Attention and Spatial studies							
Yang et al., (2018) [81]	MI	Brain controlled game	10	CSP	LDA	27 channels: (F7, FT7, T3, TP7, T5, F3, FC3, C3, CP3, P3, O1, FZ, FCz, Cz, CPz, Pz, O2, P4, CP4, C4, FC4, F4, F8, FT8, T4, TP8, T6)	The analysis of band-power outcomes showed that participants' attention level increased throughout the experiment performing MI tasks.
Promsorn et al., (2017) [89]	MI	Spatial ability test	9	N/A	FFT	1 channel: (FP1)	Participants have shown significantly mean improvement in speed, memory, attention, flexibility and problem solving, respectively.
Jeunet et al., (2015) [92]	MI	Left-hand MI, Mental Rotation, Mental Subtraction	18	CSP	sLDA	30 channels: (F3, Fz, F4, FT7, FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8)	Users' profiles can influence their MI-BCI control levels.
BCI-based Attention and Memory studies							
Qian et al., (2018) [83]	N/A	BCI-based attention training game	66	N/A	N/A	2 channels: (FP1, FP2)	The BCI sessions improving the behavioral skills of ADHD children.
Lim et al., (2012) [110]	N/A	BCI-based attention training game.	20	N/A	N/A	N/A	Inattentive and hyperactive-impulsive symptoms improvement in ADHD children.
Nan et al., (2012) [117]	N/A	Short term memory tests	32 total 16 NFT 16 CG	N/A	N/A	1 channel: Cz	Significantly higher forward and backward digit span in the neurofeedback training (NFT) group than the control group (CG).
BCI-based Spatial and Visuospatial studies							
Hammer et al., (2012) [106]	MI	Performance, personality and clinical tests and the vividness of movement imagery questionnaire.	83	CSP	LDA	128 channels cap	Predicted accuracy between the classes: 74% (left hand, right hand, right foot).
Hammer et al., (2014) [111]	MI	Performance, personality and clinical tests.	33	N/A	N/A	16 channels: (FP1, FP2, F3, Fz, F4, T7, C3, Cz, C4, T8, CP3, CP4, P3, Pz, P4, Oz)	Predicted accuracy between the classes: 79% (right hand, left hand, both feet).
BCI-based VR Gaming with Cognitive tasks studies							
Bulat et al. (2020) [93]	P300	Control machine shooting monsters.	45	CSP	LDA	16 channels: (Fp1, C3, C1, Cz, C2, C4, CP3, CP1, CP2, CP4, P1, Pz, P2, O1, Oz, O2) References: (A1, A2)	The mean accuracy across all the participants and all the sessions was 69.3%
Dey et al. (2019) [94]	-	Visual search scene.	14	TFR	Monte Carlo cluster	6 channels: (Oz, O1, O2, Pz, P3, P4) Alpha wave recording	System that adjusts the degree of difficulty according to the performance of the cognitive load of the brain.

MI: Motor Imagery, CSP: Common Spatial Pattern, TFR: time-frequency representations, LDA: Linear Discriminant Analysis, FFT: Fast Fourier transform, ADHD: Attention Deficit Hyperactivity Disorder.

test with four main common types of spatial abilities which are spatial perception, spatial visualization, mental folding and mental rotation. Participants demostrated significantly mean improvement in speed, memory, attention, flexibility and problem-solving skills when executing an EEG-based spatial task [89].

It should be noted that the operation of BCI devices is based on procedural learning, i.e., learning that mediates the automatic execution of tasks, e.g., learning to ride a bike. An efficient training technique and distinct EEG patterns provide the user with feedback indicating whether she is achieving high BCI control performance and therefore continue with the same strategy or whether she should make more effort to improve performance. This feedback reinforces the procedural training process. There also seems to be a growing number of BCI studies showing movement control generated by the EEG signals using evolutionary algorithms adapted to the user's case to handle BCI systems without moving limbs or muscles [91]. A BCI system that uses a variety of brain mechanisms, like alphabetic ordering, arithmetic, letter synthesis, etc., can train people how to generate the appropriate EEG patterns to rehabilitate their kinetic operations. For example, in one study, participants improved their level of attention by observing signal characteristics generated by more realistic images compared to less realistic images [81].

Despite its promise for improving cognitive skills (a topic we discuss further in the next section), BCI has to overcome a number of challenges. The biggest one is to maintain the user's interest and motivation to engage with the task while using tasks that are difficult enough for each user in order to increase the adaptability of the brain [90]. In addition, some issues still need to be explored, e.g., how EEG-based neurofeedback that improves perception, visuospatial attention and visuospatial memory in healthy individuals could be used with patients, and how such patients can benefit more from the training [80].

D. BCI-VR GAMING AND COGNITIVE TASKS

The application of BCI in games and in education not only leads to fun ways of interaction, improving thus involvement and entertainment, but it can also lead to the improvement of cognitive skills [93]. The P300 BCI is one of the most accurate BCIs available and is associated with a higher level of gaming-specific attention processes. It can also be an index of mental workload and cognitive training [93].

Bulat et al. [93] investigated whether cognitive functions of healthy adults can be improved by playing a P300-BCI-VR based game. A total of 45 healthy participants (25 females and 20 males) between 18 and 37 years old were recruited for the study. Participants were randomly assigned to three groups: the experimental group (P300+VR), the active control group (VR game), and the passive control group (VR movie). The experiment consisted of 5 sessions across a period of 2 weeks. At the beginning, all participants performed a series of cognitive tests, which were then repeated after the 1st, 3rd, and 5th training sessions. Significant changes in cognitive performance were shown after 5 experimental sessions for the experimental group in comparison to both other groups in tasks associated with inhibition and visuospatial attention. Specifically, it was found that the experimental group achieved shorter reaction times than the active control group and the passive control group in a flanker task that requires responding to a stimulus while ignoring distractors and in a visual search task.

In another study, Dey et al. [94] created an adaptive visual search task in VR based on real-time interpretation of the user's EEG. The system adapted to the cognitive load difficulty in real-time based on the effort made by the user. To enable the visual search task adaption participants performed two blocks of n-back trials, first a block with 1-back trials and then a block of 2-back trials, while task load was measured. The n-back task shows a sequence of numbers and asks participants to recall the number that is n positions back from the current number. For example, a 2-back task asked people to recall the 2nd number before the current number was shown. The use of 1-back and 2-back tasks allowed the researchers to obtain an index of the participants' brain activity in relation to an easy and a difficult working memory task respectively, and thereby to calibrate the task difficulty parameters. This was accomplished by taking the mean alpha power induced by these two n-back blocks to calculate a baseline for each user and to use this baseline value to adapt the visual search to their task load. When the task load was above the mean level of the two calibration tasks, the researchers decreased a level and increased it when task load was lower. This process ensured that the adaptation was customized to each individual's cognitive state. This way, the researchers succeeded in creating a system that adjusted the level of difficulty according to the cognitive load [94]. Overall, the results from the studies reviewed indicate that BCI gaming combined with VR can be used for improving cognitive functioning in healthy participants, producing effects that are over and above those achieved by cognitive training.

V. CHALLENGES AND DIRECTIONS

Although BCI has been widely used in the scientific community, it still faces many challenges in attracting commercial interest and being adopted by the general population (see TABLE 6). These challenges must be addressed from the community of BCI in order to achieve more improvements.

A. TECHMOLOGICAL CHALLENGES

Operating an MI-BCI system usually requires a large number of training trials, thus making the training phase required to create a realistic model time consuming. However, when users are taught properly, MI strategies often deliver remarkable results. Thus, efforts should be concentrated on reducing calibration time and promoting effective training. Clever gamification techniques that will keep the user's interest high during the training sessions may help to this purpose. Also, because EEG signals are non-linear, non-stationary, and artifact-prone, the accuracy of multiclass BCI, especially with MI is very low, around 65-70% [54]. Therefore, one may think about using different BCI paradigms like the P300 or the SSVEP.

The P300 has higher average Information Transfer Rates (ITR) and does not require a special training process. However, depending on the severity of the impairment, the P300 may be affected. A large number of studies have found that even people with Amyotrophic Lateral Sclerosis (ALS) and Locked-In-Syndrome (LIS) are capable of handling BCI-based P300 for long periods of time. But generally, healthy individuals exhibit higher ITR [95]. Notably, with both healthy users and patients, the experimental procedure requires the assistance of trained personnel. In addition, the need for elaborate instructions in a BCI system using the P300 paradigm lengthens the time of the intervention, which results to reduced total performance. Pairing general models with real-time training can be a good approach to decrease the calibration period and boost P300 accuracy along with user entertainment [96]. Unfortunately, the P300 paradigm requires flashing external stimuli, making it difficult to use in realistic scenarios that mimic everyday life. Furthermore, even after relatively short periods of use, users experience eye strain while people with vision impairments exhibit very low performance.

The SSVEP approach requires almost no training or calibration. Hence, although this BCI paradigm is faster than P300-based systems, due to the inherent flickering, it has the same drawbacks as the P300. That is, it is difficult to use in everyday life, causes eye strain, as well as low performance in people with vision problems. Moreover, some participants produce very poor SSVEP responses.

BCI games are slower and less accurate than conventional interfaces. Therefore, it seems some important issues must be resolved before the general population accepts BCI games. A popular challenge is the use of the most appropriate BCI paradigm depending on the case of the application. Among MI, P300, and SSVEP paradigms, the P300 seems to be preferred by the research community for BCI games. Although the P300 modality is often employed in puzzle games, it needs to be upgraded so that it can be used extensively for other game types too, such as action games with locomotion. The accuracy of real-time BCI systems with moving users seems to be low. When the users are walking, the P300 peak is generated, but the overall system performance decreases dramatically [97], [99]. Therefore, in games where there is movement of a character, controlling the games with MI might be preferable.

In addition, one of the biggest challenges to be faced is BCI illiteracy. Indeed, around 15-30% of the population find it difficult to use MI (i.e., they produce low-quality brain signals), making this an additional obstacle to the general use of BCI systems [6]. The quality of EEG signals can be increased in cases where additional training strategies are used to present the user with performance feedback.

Also, physiological factors such as the heart rate can significantly affect the EEG features. In real world, a plethora of sensory stimuli in the environment (e.g., noise, distractions, communication wave flows, etc.), as well as movement, can affect the quality of brain waves. Therefore, when designing a BCI system, developers should take into account the specific environment in which the proposed application will be used. Therefore, at the system design phase, it is important to investigate in depth the nature of the users, basic system criteria, and environmental aspects.

B. PSYCHOLOGICAL AND NEUROLOGICAL CHALLENGES

Different brain-related factors such as brain anatomy and neuron activity that are associated with mental processes, brain physiology and emotion, also known as neurophysiological factors, have a critical role in BCI performance and cause important variability between individuals [98]. Also, further psychological aspects like memory, attention, cognitive load, tiredness, as well as key individual characteristics such as gender, age and lifestyle, affect the moment-to-moment dynamics of the brain [99], [100]. People with lower empathy for example, are less emotionally involved in a P300 paradigm and may generate better EEG patterns than individuals with higher empathic engagement [101], [102]. In addition, physiological parameters of the resting state (e.g., heart rate and resting state frequency characteristics) affect the performance of BCIs [103]. Furthermore, complexity and variety in the brain, create a highly unstable neural connection over time and variability among participants [104]. An effective BCI system must be robust to such possible physiological oscillations to allow more generalized use [98], [99].

Sensorimotor-based BCI is based on spectral power density and spectral entropy, resulting from resting state EEG recordings that also affect BCI accuracy [105]. Psychological prognostic factors, like motivation, concentration, and attention, are also related with Somatosensory motor-based BCI performance [106]. About 15-30% of people cannot generate strong brain signals to control a BCI [6], [107].

Examination of neurophysiological factors could decrease BCI illiteracy. The existence of BCI illiteracy is not based solely on the user's ability to generate signals. Sometimes technical constraints may prevent the estimation of key features for a successful BCI operation. For example, scalp EEG measurements may not present distinct patterns in the EEG signals due to the cortex folding or the distance from the scalp to the cortex [99], [108]. Thus, additional case studies are needed for monitoring neurophysiological variants that could contribute to BCI improvement.

Finally, targeted BCI design is required to tackle specific brain lesions such as those found in stroke, where for each specific case, residual brain function for rehabilitative interventions should also be taken into account [109], [118].

C. GAMING CHALLENGES

Gaming integration into BCI systems is a promising way to increase engagement and promote training with BCI systems. However, various issues still need to be resolved. Although BCI-gaming strongly motivates people to become engaged, nevertheless users have very poor performance and speed compared to classic systems. Also, when the users walk or move their limbs, the overall performance drops dramatically [67], [85]. Since there's a growing interest in games that will motivate and excite users to get more involved, the need for a case-specific BCI game design based on the personal interests of each user becomes imperative.

As reviewed here, cognitive games have been shown to improve certain cognitive functions, especially those related to perception, visuospatial attention and visuospatial memory [98], [99]. However, it is a great challenge to turn a cognitive task into a serious game while keeping its underlying function intact. VR seems to be a promising approach for cognitive gaming as it allows turning laboratory tasks to fun and entertaining games.

TABLE 6. Summary of technological, psychological and neurological, and gaming challenges.

Technological Challenges		
Motor Imagery	**P300**	**SSVEP**
Calibration period reduction.	The performance over time may be affected.	Flickering external stimuli making it difficult to use in realistic scenarios.
Effective training strategies.	Healthy individuals attribute higher ITR.	After relatively short periods, individual feel pain and fatigue in the eyes.
Clever gamification techniques.	Flashing external stimuli making it difficult to use in realistic scenarios.	People who have vision problems have very low performance results.
Keep the user's interest during training sessions.	After relatively short periods, individual feel pain and fatigue in the eyes.	
Very low accuracy especially in multiclass BCI.	People who have vision problems have very low performance results.	
Gaming Challenges		
The accuracy and speed of the games is very low compared to conventional interfaces.		
When the users are walking or moving, the overall performance drops.		
A case-specific BCI design.		
Motivation to engage taking advantage of the gaming.		
To keep the interest while performing the cognitive tasks.		
Take advantage of virtual reality.		
It's difficult to convert a cognitive task into a serious game and keep the nature of the task.		
Psychophysiological and Neurological Challenges		
Psychological factors such as Attention and Memory Load influence instantaneous brain dynamics.		
Fatigue and competing cognitive processes cause EEG signal noise.		
Elimination of BCI illiteracy.		
Factors such as different levels of cortisol in the body and heart rate variability can significantly affect the features of EEG signals.		
Various sensory stimuli exist in the environment outside the laboratory, which can affect the quality of brain waves.		
BCI performance may be affected by the features of the frequency domain in resting state and variability of the heart rate.		
The Psychological predictors of attention and motivation, are associated with the performane of BCI sensorimotor rhythm.		

VI. DISCUSSION AND CONCLUSION

BCI-VR technology provides a promising way to improve the quality of life for patients in different conditions. It can, for example, help people with mobility problems to better handle prosthetic limbs, or to facilitate the rehabilitation process for stroke patients and patients with neurological conditions. Compared to standard BCI systems, BCI-VR systems don't need many extra tools to configure the environment, because the use of VR can accurately simulate the conditions of the actual rehabilitation environments. In addition, it provides more safety during its use and can provide easy and fast simulation of repetitive processes. Also, useful real-time feedback can be presented to motivate users and to improve, as a result, user performance. Indeed, BCI-VR technology can increase the classification accuracy of the system and decrease the training duration of the individual.

Despite the many important breakthroughs in BCI research, some issues still need to be resolved. Reactive BCI that relies on external stimuli is almost unlikely to be established in the real world, despite the little training required by the user and the high exhibited performance. What it is mostly expected, is a more endogenous way of commanding an action to be executed successfully with active BCI. Unfortunately, commercial products are far from being widely used in the physical world mainly due to low performance and the long training required. Also, various external factors and stimuli make it difficult to decode the signals for the correct command. Research is typically carried out under favorable laboratory conditions that differ markedly from those of daily life. Technologies such as VR could therefore be utilized to create realistic environments that simulate real-world conditions for better training and adaptation to the BCI.

In recent years there has been a huge improvement in algorithms in the field of BCI, especially in machine learning techniques. Nevertheless, we should also look at how we could eliminate BCI illiteracy through cognitive tasks in order to increase performance [119]. In addition, there is a need for BCI applications where users will not need specially-trained personnel to help them fit the device for the training and use the application. Instead, there must be complete autonomy from the user to use BCI without help from a caregiver.

New technologies supported by 5G systems and beyond have great potential for VR higher quality communication with significantly lower delays as in real-time processing. The high-speed communication channels enable the VR applications to load high amount of data in the cloud/edge servers to store and use with strict time constraints [123].

In closing, we should note some limitations of our current review. One limitation is that we have focused our search to a very specific part of the BCI domain. That is, we have only studied specific systems that are non-invasive and based on EEG. Beyond these systems, one may consider BCI systems that rely on ECoG, fMRI, EMG, fNIRS, etc. We also focused only on studies that combined BCI with VR Gaming or BCI with cognitive tasks based on spatial perception, spatial memory and attention. Of course, there are BCI systems that focus on other cognitive mechanisms that relate to emotions, social skills, communication, etc. At the same time, only 3 BCI paradigms have been studied, those that have been extensively used in the BCI-VR Gaming category, namely MI, P300, SSVEP. The reader might also want to explore systems that are based on slow cortical potential, error related potentials, etc. In conclusion, this review focuses on a very specific field of the BCI area and is therefore most useful to researchers interested in at least 2 of the 3 parts of the triptych, "VR cognitive Gaming based on BCI using EEG".

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