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Review

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Review

Integration Between Serious Games and EEG Signals: An Overview

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Abstract: A serious game combines concepts, principles, and methods of game design with information and communication technologies, for the achievement of a given goal beyond entertainment. Serious game studies have been reported under a brain-computer interface (BCI) approach, with the specific use of electroencephalographic (EEG) signals. This study presents a review of the technological solutions from existing works related to serious games and EEG signals. A taxonomy is proposed for the classification of the research literature in three different categories according to the experimental strategy for the integration of the game and EEG: (1) evoked signals, (2) spontaneous signals, and (3) hybrid signals. Some details and additional aspects of the studies are also reviewed. The analysis involves factors such as platforms and development languages (serious game), software tools (integration between serious game and EEG signals), and the number of test subjects. Based on the definition, categorization, and state of the art, the main research challenges and future directions for this class of technological solutions are discussed.

Keywords: serious game; brain-computer interface; BCI games; electroencephalography; signal processing

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1. Introduction

The propensity or inclination to consume video games has changed, breaking paradigms and stereotypes related to the gender and age of players, becoming one of the popular forms of entertainment for millions of people and generating an increase in the number of games [1]. According to findings from the Global Entertainment & Media Outlook 2018-2022 report by consulting firm Price Waterhouse Coopers (PWC), video games and e-sports games will be one of the industry's fastest-growing segments. In addition, the firm presents the four main revenue categories in the global video game and e-sports market that will grow respectably until 2022: revenue from traditional games, social or casual games, video game advertising, and e-sports [2].

Video game consumption patterns among young people reflect specific demographics trends. In Latin America, and particularly in Colombia, young people between 16 and 24 years old constitute the most active segment, followed by the groups of 25 to 34 and 35 to 44 years old [3]. Speaking about Colombia, a 2022 report indicated that video games have already become a daily necessity for 37% of Colombians [4]. Their figures indicate that 41% of people have at least one video game console in their home, and 6 out of 10 respondents said they play video games regularly. In terms of gender [3], women represent 52.2% of players, while men constitute 47.8%. The predominant age of the players is 25 to 34 years old, followed by the range of 35 to 44 years old and 16 to 24 years old. This indicates that the activity is not limited to the youngest. Several studies about the consumption of video games have been carried out in Colombia such as a study in Medellin (Colombia), focusing on games about violence and drug trafficking [3], the relationship between video games and obesity [5], school performance and video games [6,7], and toxic behaviors [8], among others.

The versatility of video games allows them to be part of different environments, not only providing entertainment but also as "playful instruments to achieve a desired objective, that is, learning effect,

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training or a better state of health " [9]. The above allows us to introduce the concept of a serious game, which has been applied in training and simulation, digital education, vocational or workplace training, marketing and advertising, health or awareness, and social impact. In general, a serious game combines concepts, principles, and methods of game design with information and communication technologies (ICT) and with specific methods and technologies, taking into account the objective of the game [10]. It is important to highlight that typical information and communication technologies (ICTs) include aspects related to artificial intelligence for automatic game control; aspects of human-computer interaction (HCI) for game control and input/output (I/O) devices; sensor technology to retrieve context information (user/player); multimedia aspects; usability and gaming experience features; among others [9]. This is reflected in some commercial gaming devices that offer several ways to interact with games, either as stand-alone controllers or in hybrid modes [11] and in research where the relationship between serious games and HCI can be evidenced, under an approach based on brain-computer interfaces (BCI), specifically using electroencephalographic (EEG) signals.

The use of brain EEG signals with serious games is a recent trend in research [12–15]. The existence of new types of EEG sensors available for game development makes it possible to adapt games that use recognition of brain states [16]. Research that links serious games with EEG signals contemplates several objectives, among which the following stand out: (1) Test paradigms about BCI, (2) control video games, (3) design and implement neuro-feedback games, (4) train or test video game users, (5) develop e-learning programs and medical applications (explore brain activities in certain disorders such as anxiety, autism), (6) activate EEG signals from serious games (7) relate psychological components with physiological measurements, (8) compare traditional health equipment with low-cost equipment and (9) test EEG signal analysis methods. Several review articles have examined and analyzed serious games under a BCI approach. In [17], they present an investigation of BCI games according to the game genre (action, strategy, role-playing, adventure, sports, simulations, and puzzle games) to evaluate the suitability of game genres in the main BCI game implementations and introduce the term gameplay as the key aspect to consider in game development.

In [18] they examine neuroscientific studies on computer games, serious games, and virtual environments for learning processes, including attention, cognitive workload, sense of presence, and immersion. In the work of Ahn et al.[19], based on the review and search of literature carried out in the field of BCI games, they identify that BCI control paradigms that use EEG signals have been the main focus of research. Also, they conduct an opinion survey of researchers, developers, and users and propose three important elements in the expansion of the BCI games market: standards, playability, and appropriate integration. For their part, Kerous et al. [20] present an analysis of BCI research progress focusing on EEG-based video game applications, considering the extent of research in the field and the numerous benefits provided by such interdisciplinary research efforts. Considering the focus of the previous reviews, it is clear that they have provided useful and detailed information on the aspect they wish to highlight. BCI games are available in terms of BCI control paradigms, game genre, or in terms of applications. This review focuses on the experimental strategy implemented in the integration of the serious games and EEG system. Motivated by the trends in serious games, the development of low-cost equipment for EEG signal acquisition, the increase in commercial devices for video game interaction, and applications involving serious games and EEG, this article aims to review and present technological solutions of existing works that link serious games and EEG signals. To this end, the method used for the literature search is described, definitions of serious game, BCI, and EEG signals are provided as previous concepts, and a taxonomy is proposed that allows the classification of the existing works and research into three different categories according to the experimental strategy implemented in the integration of the serious game and EEG system. For the work in these categories, details are presented on platforms and development languages (serious game), software tools (integration between serious game and EEG signals), and the number of test subjects; which allows for the integration of findings from different research projects. Finally, the main research challenges and future directions are discussed.

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2. Literature Review Process

This literature review is based on works representing a contribution to scientific-technological development that have been subjected to scientific peer review. Articles written in English-language journals are included (conference proceedings, research articles, reviews, and surveys), and chapters in periodical publications and conferences. The search was performed in the following databases or bibliographic tools: Scopus, Tree of Science, Web of Science (WoS), IEEE Xplore, Pubmed, Redalyc, Scielo, Science Direct, Springer Journal and Google Scholar, using the following keywords and operators: ("electroencephalography" OR "electroencephalogram" OR "EEG" OR "Brain-computer Interfaces (BCIs)" OR "Brain-computer Interaction" OR "Interface") AND ("control" OR "controlled" OR "for controlling" OR "used" OR "based") AND ("game" OR "video game" OR "serious game" OR "gaming application" OR "computer games"). A total of 105 articles on systems and methods were found. After a first examination of these articles, those not directly related to the topic of interest were excluded. As a result of the search and selection process, fifty-nine articles were classified for the analysis. Sixteen of the articles were categorized based on the experimental strategy implemented in the integration of the serious game and EEG system. Figure 1 presents the flow chart describing the strategy for the performed bibliographic search.

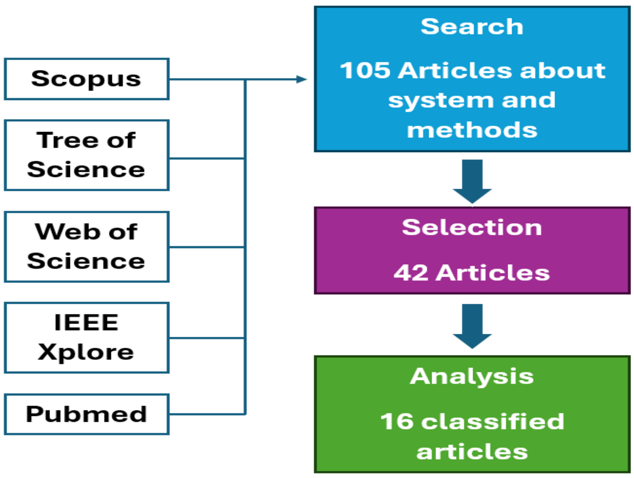

Figure 1. Bibliographic search flowchart

3. Foundations of Serious Games in EEG-Based BCI Systems

3.1. Serious game

Several attempts have been made to define serious game [21–25]. However, there is no universal or widely accepted definition to date. In this work, we use the definition proposed by Göbel [9], which specifies serious game in the following way: "playful instruments to achieve a desired objective, that is, learning effect, training or a better state of health." On the other hand, we unify the serious game concept by including related terms such as video games, computer games, neurogames, BCI games, and neuro-feedback games. Regarding the fields of application, Alvarez et al. [26] propose 5 categories to classify serious games: educational training, advertising, edumarket, political games, and training and simulation games. For their part, Alvarez and Djaout established a classification system based on three criteria: Gameplay or playability (G), Purpose (P), and Sector (S); forming "the G / P / S model", which can be a guide to classify serious games taking into account their playful and serious dimension [24]. In contrast, Göbel [9] indicates that the fields of application may include training and simulation, digital education, vocational or workplace training, marketing and advertising, health (for prevention and rehabilitation), or awareness and social impact (involving issues of politics, security, religion, energy or climate). The former works show that some taxonomies that have been proposed vary according to the principles, methods, and purposes of the classification. However, they are useful

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tools for classifying serious games. It depends on the criteria of the researcher and the specific field of his work to be guided by one classification system or another.

On the other hand, it is important to highlight that applications in serious games combine concepts, principles, and methods of game design with information and communication technologies (ICT) and specific methods or technologies (involving the objective of the game). Typical ICTs include artificial intelligence for automatic game control; human-computer interaction (HCI) aspects for game and device control (I/O); sensor technology to retrieve context information (user/player); multimedia aspects; usability and game experience features [9]. All these technologies can be found in several research works [27–32] . This work focuses its study on Serious games under an approach based on brain-computer interfaces (BCI), specifically using electroencephalographic signals (EEG).

3.2. Brain Computer Interfaces (BCI) and Electroencephalography (EEG) Signals

The central nervous system (CNS) is composed of the brain and spinal cord; it is characterized primarily by its location within connective tissue membranes (meninges), by its distinctive cell types and histology, and by its function, which allows it to integrate a large number of sensory inputs to obtain effective motor outputs [33]. Now, the activity of the CNS includes electrophysiological, neurochemical, and metabolic phenomena (such as neuronal action potentials, synaptic potentials, neurotransmitter releases, and oxygen consumption). These phenomena occur continuously and can be monitored by measuring electric or magnetic fields, hemoglobin oxygenation, or other parameters using sensors on the surface of the brain or inside the brain [34]. Under the previous context, the term Brain-Computer Interface (BCI) is introduced, which can be defined in different ways [35–38]. In general, a BCI system measures brain activity and translates it into control signals, which are used in the construction of new technologies that allow for improving the quality of life of people (healthy or disabled) [39–41]. Devices that only monitor brain activity and do not use it to modify the ongoing interactions of the CNS with its environment are not considered BCI.

The design of a BCI includes interdisciplinary knowledge, covering areas such as computer science, engineering, signal processing, neuroscience, and psychology. In general, two stages are required to use a BCI: (1) a training stage, in which (a) the user is trained to voluntarily control his or her brain potentials (in the case of the BCI operating condition), (b) an offline training stage, which calibrates the training algorithm (in the case of BCI pattern recognition), and (2) the online stage, in which the BCI system is used for control [42]. In online mode, the BCI system can be compared to a closed loop, which involves steps or tasks related to the control signals obtained from the brain: acquisition or measurement of brain activity, pre-processing, feature extraction, classification, translation into a command and feedback [36,42,43] . Therefore, control signals obtained from the brain can be considered as the object of study in BCI systems. These signals can be presented in three categories: Evoked signals, spontaneous signals and hybrid signals [20,37,44–46].

Furthermore, Lotte et al. [43] and Ramadan et al. [37] consider that BCIs can be classified taking into account three aspects: reliability, invasiveness, and synchronization. Regarding reliability, BCIs can be dependent or independent, considering whether a certain level of motor control is required by the experimental subject. Invasiveness refers to the way brain activity is measured or acquired (invasive, non-invasive, semi-invasive). Synchronization refers to the fact that the user's interaction with the system takes place within a certain period (synchronous) or the user is free to perform an activity or task at any time (asynchronous). In contrast, Martišius and Damaševičius divide BCI applications into two categories: medical applications and non-medical applications. The first category includes rehabilitation and control of prosthetic devices, medical diagnosis, assistive mobility, BCI-controlled web and music browsers, and mental status recognition; while non-medical BCI applications refer to video games, multimedia, or virtual reality [42].

Based on the previous arguments, and considering the area of study of serious games, we limit this review work to dependent, non-invasive, and synchronous BCIs. Regarding the selection of electroencephalography (EEG), this is considered the most common method for recording brain

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signals; it is non-invasive, is implemented in low-cost equipment, offers good communication and control channels, high temporal resolution, is safe, easy to use and affordable [37,47]. Furthermore, EEG-based devices have become fundamental elements in the design and development of serious games, allowing them to meet consumer demands in terms of wearability, price, portability, and ease of use [48].

Electroencephalography (EEG) is a technique for recording electrical activity or voltage changes resulting from ionic currents within brain neurons [49]. EEG signals are sinusoidal waves with amplitude typically between 0.5 and 100 μv (peak-to-peak) [50]. EEG signals are generally described in terms of rhythmic and transient activity. On the other hand, active or passive electrodes placed on the scalp are used to measure the EEG signal, considering international systems or standards for their location [51,52]. There are several EEG signal processing techniques for evoked, spontaneous, and hybrid signals [46,53], along with software tools for their analysis, thus offering different forms of interface and processing style [54]. In conclusion, the signal generated through the activity of the brain occurs as a result of thoughts or intentions [55,56], and that signal acquired using EEG has useful information that can be converted into commands in a serious game that is the subject of interest of this item.

4. A Review of Technological Solutions that Integrate Serious Game and EEG Signals

According to the literature review, research integrating serious games and EEG signals has several objectives, among which the following stand out: (a) Test paradigms about BCI, (b) control video games, (c) design and implement neuro-feedback games, (d) train or test video game users, (e) develop e-learning programs and medical applications (explore brain activities in certain disorders such as anxiety, autism), (f) activate EEG signals from serious games, (g) relate psychological components with physiological measurements, (h) compare traditional health equipment with low-cost equipment, and (i) test EEG signal analysis methods. On the other hand, in the research of existing works, three different categories of BCI systems are distinguished according to the experimental strategy implemented in the integration of the serious game system and EEG: (1) experimental strategy based on evoked signals, (2) experimental strategy based on spontaneous signals and (3) experimental strategy based on hybrid signals. The experimental strategy not only determines what the BCI user must do to produce the brain patterns that the BCI can interpret, it additionally establishes restrictions on hardware and software and even defines the training required [44]. Experimental strategies are associated with different types of brain signals; the most common are evoked and spontaneous ones [44,45,53], however, we include hybrid signals in this work [37]. Table 1 describes the technological solutions of 16 existing works related to serious games and EEG signals. Based on the above taxonomy, existing works are presented by separating them into 3 categories according to the experimental strategy.

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Table 1. A classification of technological solutions integrating serious games and EEG signals

Article	Strategy	Serious Game Tools	Software	Testing subjects
[50]	Evoked signal	Engine for 3D graphics. Engine for acquiring and processing data	Programming and platform, network communication engine in C#	6
[51]		Unity3D	Python	25
[10]		Unity 3D	NeuroSky algorithm, Emotiv development kit	62
[36]		OpenViBE	OpenViBE environment. Emotiv Development Kit (EDK) written in C. (API) in C++, C#, Java and MATLAB.	2
[42]	Spontaneous signal	SDL and Panda3D	Visual C++	5
[53]		C#, Unity 3D, Visual Feedback. (Photon Network API)	Matlab module and control signal generation unit.	3
[54]		C#	Matlab	-
[55]		C#	Xavier TechBench Software, Matlab y Emotiv EPOC+ API.	12
[56]		-	-	14
[57]		-	Matlab	24
[58]		-	OpenVibe. Matlab and EEGLAB. RehabNet Control Panel and Virtual Reality Peripheral Network (VRPN) Protocol	20
[11]		Unity3D	EMOTIV open source SDK.	-
[59]	Hybrid signal	-	MATLAB BCI to Virtual Reality Toolbox or BCI2VR.	5
[60]		Unity3D	NIA Software	-
[61]		Unity3D	Bio-Cirac. Open ViBe.	700
[40]		Unity 4- C#.	Matlab. protocol TCP / IP	5

4.1. Experimental Strategy Based on Evoked Signals

The experimental strategy based on evoked signals is characterized by requiring external stimuli (auditory, somatosensory, or visual) [44,62,63]; the user focuses attention on a set of stimuli that produce an autonomous response that can be detected by the BCI system. Therefore, the evoked signals are generated unconsciously by the subject when receiving external stimuli [37]. Lalor et al. [57] presented an EEG-based brain-computer interface design for binary control in an immersive 3D game. To do this, they relied on the steady-state visual evoked potential (SSVEP) in a real-time gaming framework. Van Vliet et al. [58] aimed to create a BCI that allows the operation of a game by issuing explicit commands with low-cost consumer equipment, based on the detection and classification of the users' SSVEP response. Additionally, they compare the research-grade EEG device (IMEC device)

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versus a commercially available device for any user. In [11], they examined the effectiveness of two different BCI devices to fully control an avatar within a serious game and presented 3 objectives: to fully control an avatar in real-time using only EEG data, to qualitatively examine the different behavior and reactions of users while playing the game, and to test 2 EEG signal acquisition devices. Experimental subjects were visually stimulated by fully controlling an avatar in the game, switching cognitive states such as meditation and attention. In [42], they aimed to explore BCI technology as a game controller option, therefore, they used EEG signals to control a real-time BCI game prototype based on SSVEP. The purpose of the experiment was to develop a system that uses brain activity to offer control within a real-time environment to evaluate signal processing algorithms.

4.2. Experimental Strategy Based on Spontaneous Signals

In this strategy, the user performs a mental task such as imagined movement or counting or subvocal counting to create changes in brain signals that can be detected by a BCI [53]. Therefore, spontaneous signals are generated by the subject voluntarily without any external stimulus. Wang et al. [48] presented the design, algorithm, and implementation of two new EEG-based 2D and 3D concentration games using a fractal dimension model. The experiment was designed to be able to classify two brain states (relaxation and concentration). Khong et al. [64] propose a video game that allows multiple users to connect to the same application in a 3-D environment controlled by EEG characteristics. In this work, EEG signals were related to 3 different levels of attention and traditional control mechanisms such as the keyboard. The authors identified that the main motor rhythms in EEG connected to attention and memory correspond to the theta (4-8 Hz), and alpha (8-12 Hz) beta (13-20 Hz) bands of EEG. Kawala-Janik et al [59] designed and developed a human-machine interface (HMI) to control a game based on the implementation of bio-signals. For this research (first phase) they decided to record brain signals and also voice recognition as an additional tool for control. The μ waves were analyzed because they are related to events that occur only during an imaginary and real motor action, which have a frequency similar to α waves.

Besides, Mondéjar et al. [60] measured brain wave activation through an electroencephalogram to relate psychological components with physiological measurements. From the EEG signal recording in the experiment, which presents a psychological evaluation phase and a phase of playing video games, the activation of different band frequencies or waves emitted by the brain (theta, beta, alpha, and delta) were observed along with the area in which they are most active. In the study by Asensio-Cubero et al. [61] explored the viability of applying a multi-resolution analysis (MRA) on the graphical representation of EEG data for a BCI system in real-time. They designed and developed a game that can be controlled by imaginary movements of the limbs to test EEG signals. In [65], the authors created a serious game to measure and compare people's brain activity based on beta waves when playing a serious game in 2D and 3D (beta waves are activated just when the person is concentrating). Vourvopoulos et al. [66] examined the effect of gaming experience on brain pattern modulation ability during motor imagery training and the elements contributing to high BCI control. For the experiment, users were grouped based on their gaming experience (experienced player and moderate player), and mental images of the corresponding hand (right or left) were used for game control. Alchalcabi et al. [15] presented a proposal for an EEG-based serious game that provides training to increase focus for those diagnosed with Attention Deficit Hyperactivity Disorder (ADHD) and Attention Deficit Disorder (ADD). The research contemplated two states to be trained ("push" and "neutral") and the tests were performed on healthy subjects not suffering from ADHD symptoms, who used mentally issued commands (after training) to move the avatar.

4.3. Experimental Strategy Based on Hybrid Signals

Hybrid signals are the combination of signals generated by the brain for control [37]. It is also possible to combine brain signals with other physiological signals, that is, to combine a BCI system with another system not based on BCI. This generates a topic of debate regarding whether this type of BCI strategy can be considered hybrid [67]. In this article, it is considered that the experimental strategy based on hybrid signals not only combines different types of brain signals but also brain signals with other physiological signals.

Many works employ this strategy. Huang et al. [68] proposed a paradigm for a brain-computer interface (BCI) based on 2-D virtual wheelchair control, which was implemented in a game. They relied on EEG signals associated with motor execution/imagery of hand movement, surface electromyography (EMG) over the wrist extensors to control hand movements, and bipolar electro-oculogram (EOG). Additionally, there are visual stimuli and movement intentions encoded. Hawsawi and Senwal [69] researched the capability of the Neural Impulse Actuator (NIA) controller as an alternative tool to support gamers with motor disabilities by using their brain activities (EEG), facial muscles (EMG), and eye movement (EOG) to interact with games. In [70], they propose a video game-based rehabilitation system called BKI (Brain Kinect Interface) composed of an EEG device and a Kinect sensor that allows the multimodal recording of physiological signals (EEG and kinematics). Furthermore, it uses specialized video games to increase motivation and improve the quality of service (personalization) and the recovery process. Belkacem et al. [45] consider that omnipresent problems in EEG-based BCI research such as Electro-oculogram (EOG) and Electromyogram (EMG) are valuable sources of information and are useful for communication and control. Therefore, they present a hybrid EEG-EOG BCI paradigm, which involves the classification of more than six kinds of eye movements for real-time game control, showing the utility of EOG signals in EEG data.

5. Discussion

In this review, it was found that the experimental strategy based on spontaneous signals is most frequently used. It could be said that spontaneous signals are preferred because they provide high degrees of freedom in association with real and imagined movements of hands, arms, feet, and tongue [71]. In addition, due to the independence of external stimuli, they are preferable in control applications and provide the user with direct control [72,73]. According to [42], the biggest challenges are related to accuracy, speed, price, and usability. However, the training phase in BCI systems is another challenge faced by researchers in EEG-based games. Training both the user and the system requires long and repetitive trials that often result in fatigue and poor performance.

Additionally, many users cannot voluntarily modulate the amplitude of their brain activity to control the neuro-feedback circuit. In this context, due to the large variability of individual EEG signals, it is almost impossible to have a single universal training for different brain signals [15] and to develop "universal" neuro-feedback systems that can be applied to all users without the need for some time-consuming customization or individualization [74]. There are different types of games and degrees of complexity in the design, development, and implementation of serious games. Some research has hypothesized that experienced players might have better performance when using a BCI system because they have developed visio-motor skills derived from the game [66,75,76]; this aspect can be taken into account when designing the experiments.

Most serious games integrated with EEG systems are still in the prototype stage, and this may be the reason for the small groups of users in the proofs of concept. Often, the number of people involved in the experiments does not correspond to a representative sample that allows for validating the system or even performing a statistical analysis. On the other hand, there are many aspects generating discrepancies and controversies among investigations. Comparison of research results is difficult due to factors such as variability in EEG signal acquisition systems, methodological factors, the lack of standardization in relation to experimental design and data collection, and the performance of tests for proof of concept tests.

6. Challenges and Future Research Directions

The field of integrating serious games with EEG signals presents many technical, methodological and usability challenges. One of the main challenges is related to the accuracy and reliability of real-time EEG systems. The individual variability of brain signals makes it difficult to obtain consistent and highly accurate results, especially in applications requiring complex control, such as interactive games. In addition, adapting EEG signal processing algorithms that can be generalized to different users, rather than requiring extensive customization, is an important area for improving the accessibility and functionality of these applications.

From a methodological point of view, another obstacle is the lack of standardization in the design of experiments and data collection. Many ongoing studies use different approaches and parameters, limiting the comparability and reproducibility of results. The establishment of common experimental protocols and standards would facilitate the integration of results and collaboration between research groups, contributing to more consistent progress in this area.

On the other hand, designing an optimized interface and user experience remains a challenge. Despite advances in EEG technology, the interface must be intuitive and attractive to users, ensuring that the learning process is effective without distractions and interaction difficulties. A promising direction in this area is to combine EEG with emerging technologies such as virtual reality or augmented reality, which can improve immersive experiences and potentially learning outcomes.

Regarding future research directions, the need to study physiological and psychological aspects of users is emphasized in order to better understand how interaction with serious EEG-based games can affect learning and cognitive development. This would include measuring aspects such as cognitive load and attention levels, which could be correlated with game performance and learning outcomes. Finally, the creation of interfaces compatible with cloud computing will increase the flexibility and scalability of EEG systems, facilitating the analysis of large amounts of data and improving the availability of these technologies in educational and therapeutic contexts.

7. Conclusions

This review demonstrates the significant potential of Brain-Computer Interface (BCI) and Electroencephalography (EEG) integration within serious games, emphasizing applications for both neurorehabilitation and cognitive skill enhancement. Through this synthesis, it is evident that BCI-EEG systems, especially when combined with serious game frameworks, open promising avenues for interactive learning, therapeutic interventions, and assistive technology for individuals with disabilities.

The integration between serious games and EEG signals in a BCI system can be a good alternative to traditional control devices such as a keyboard or mouse, becoming an opportunity for people or users with or without disabilities. In this article, different technological solutions for the integration of serious game systems with EEG signals were reviewed and classified according to the experimental strategy. The article detailed aspects to determine the state of the research, such as application, hardware, EEG signal processing and classification techniques, software tools and development environments, description and implementation of the serious game, and proofs of concept.

One key finding is the current prototypical stage of most BCI-EEG games, which limits broader validation and necessitates further development to enhance scalability and robustness. Future research should prioritize refining these systems to allow testing on larger, diverse user groups, enabling statistical validation and adaptation to individual user needs. Additionally, exploring the psychological and physiological impacts on users could provide critical insights into optimizing user experience and engagement through adaptive feedback mechanisms.

The review also highlights a need for standardization in EEG signal processing and experimental design protocols. Standardized frameworks would facilitate cross-study comparisons, accelerating technological advancements and promoting interdisciplinary collaboration. Also, the potential integration of cloud computing within BCI-EEG systems could offer scalable data storage and processing solutions, broadening accessibility and enhancing computational efficiency across platforms. Overall, interdisciplinary collaboration among researchers, developers, and end-users is essential for advancing BCI-EEG technology in serious games. This cooperative approach will not only improve usability but

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also contribute to establishing BCI with serious games as a valuable tool for cognitive and rehabilitative applications across varied fields.

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