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Research Paper

The MEG21 Unified Model for Modern Electronic Games of the 21st Century based on Electroencephalography-controlled Brain-Computer Interface

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Abstract. The rapid advancement of Brain-Computer Interface (BCI) technology has facilitated its employment in non-clinical contexts, including games. Electroencephalography (EEG)-controlled games merge the benefits of both fields, as they can be employed in both serious and entertainment contexts due to their ludic and engaging nature, in addition to being accessible to people with physical disabilities. Despite these benefits and the overlapping of different fields, there is still a lack of representational schemes for these games, as current theoretical models can only represent BCI systems and games separately. This work introduces a unified model for games that use EEG-based BCI controls, assisting researchers in effectively developing and analyzing such games by providing a framework for instantiating their abstract, structural and functional components. Its utility and representativeness were evaluated using a selection of EEG-controlled games from existing literature, which demonstrated the model's effectiveness in classifying and detailing these games. Recurring attributes and descriptive values were also identified and organized based on the sample studies, showing how the components of the model could represent the functioning and structure of EEG-based games.

Keywords: BCI, EEG, Game, Model, HCI, Physiological Computing.

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1 Introduction

The recent evolution of Brain-Computer Interface (BCI) technologies allowed the development of novel applications both for clinical and domestic environments [Ferreira *et al.*, 2013]. Games based on electroencephalography (EEG), a specific modality of BCI, are being increasingly developed and applied in both contexts, especially because they can be played potentially by any person regardless of physical impairments, as the EEG signals are read and translated by the application directly from the brain [Wolpaw *et al.*, 2002].

In this context, EEG-based BCI are usually employed in serious games, which are developed and used for any purpose other than (or in addition to) entertainment [Laamarti *et al.*, 2014]. These games have potential to be employed in many different fields and applications, such as being a treatment option to help patients in rehabilitation [Lazarou *et al.*, 2018], helping in cognitive assessment and evaluation [Marçal *et al.*, 2022; Costa *et al.*, 2025], and training cognitive functions through neurofeedback [Friedrich *et al.*, 2014; Vasiljevic and de Miranda, 2019a,b; Monteiro and Adamatti, 2020]. However, given the evolution of BCI algorithms and the emergence of consumer-grade EEG devices, these games are also starting to be developed to be used solely for entertainment purposes [Vasiljevic and de Miranda, 2020a], benefiting both healthy and impaired players.

The development of BCI games raises challenges that are related to both fields [Kerous *et al.*, 2018; Sung *et al.*, 2012]. From the perspective of BCI, the developer must ensure that the system is precise enough to capture, process and identify the target neural mechanism (and thus, the player's intention) accurately in real time. From the perspective of games, the developer must also ensure the game flow, so that the player is immersed into the game, have fun playing it and desire to play it again, even if its purpose is not solely entertainment. Thus, it is required domain over knowledge from many different areas that are related to both games and BCI, including Signal Processing, Machine Learning and Human-Computer Interaction (HCI).

Despite the solid theoretical foundation derived from these multiple fields, there is an absence of a formal and comprehensive definition of a representative scheme for BCI games. Existing models and schemes from the literature can describe specific aspects of BCI-based systems or games, in both general and specialized perspectives. However, these models can only represent EEG-controlled games as a BCI system or as a game—not as a whole, single entity, thus neglecting the interconnected nature of these systems. To our knowledge, up to the development of this work, there were no model for representing the entirety of EEG-controlled games and the specific components, attributes and features that constitute them.

The definition of a consistent model for a given entity of interest is important for several reasons. It can be considered as a first step for unifying the terminology of the field, thus providing a common framework for researchers and developers to collaborate and increase consistency in the development of BCI games. It also facilitates the comparison of different studies and approaches, since the games they employ can be compared directly in a standardized manner. Moreover, given the complexity of the design space for BCI games (considering, for example, the range of possible control signals and interaction paradigms) and the variety of user experiences made possible by these games, a comprehensive and general model could aid game designers, researchers and developers to guide their design process, especially considering professionals coming from other fields.

In addition to these direct implications facilitated by a standard model, a common framework for BCI games can also influence in the advancement of the field by promoting further research and innovation, since researchers can build upon this model to adapt it for specific scenarios, and explore new experiment possibilities and game design ideas with novel combinations of attribute values for components, thus possibly leading to the discovery of more effective and innovative interaction for BCI games. Finally, considering ethical and privacy concerns associated with the acquisition and use of information acquired directly from the brain [Burwell *et al.*, 2017], a comprehensive model can help to identify potential ethical concerns and improvement options in each of its components. This could guide developers in creating games that caters for user privacy, ensuring responsible and ethical implementation of BCI technology in gaming.

In this sense, the main objective of this work is to describe a general model for EEG-controlled games, and to demonstrate the usefulness and representativeness of this model with BCI-based games from the literature. The proposed model intends to unite concepts and vocabulary from both fields into a single theoretical framework. This objective is guided by the following Research Questions (RQs), which also guided the development of the model:

- **RQ1**: Can EEG-based BCI games be described as a single entity, as opposed of separate BCI and game systems?
- **RQ2**: Can this model represent both the conceptual, functional and structural components of a BCI system and a game simultaneously?
- **RQ3**: Is this model adequate in representing important attributes of existing BCI-based games in comparison to existing schemes?

These research questions are motivated by our hypothesis that current schemes, by focusing on either BCI or games, do not represent the intrinsic attributes of EEG-based games that arise from the unification of both fields, especially at the conceptual and structural levels (RQ1). These definitions could help not only in characterizing, describing and classifying existing systems with a finer level of details, but also to provide a theoretical and architectural background for the development of future EEG gaming systems, both for serious and entertainment applications (RQ2). Moreover, the definition of this model does not disregard or aim at substituting existing schemes for BCI or games, especially considering the recent efforts to standardize the terminology of the field of BCI. Instead, by unifying aspects of both fields, it is capable of not only representing the fundamental characteristics proposed by these models, but also the emerging features that are exclusive of BCI-based games (RQ3).

This work is organized as follows: Section 2 presents the related work, including other models and how they are related to our study; Section 3 describes the proposed model and its development process; Section 4 presents a demonstration of the model using games from the literature; Section 5 discusses the results of the demonstration and the implications of the model for the literature; and Section 6 concludes the paper.

2 Related work

Studies related to the current work present models, frameworks or conceptual schemes regarding games, BCI systems and BCI-based games. For both fields, there are examples of abstract models and frameworks for representing those systems in a general or specific manner, given that they can be applied in a number of different contexts depending on their purpose. It is reasonable to assume that there is a higher number of models for representing games, given that the field of games is relatively older than the field of BCI. We will focus on describing those that are closely related or pertinent to the scope of this work.

For the field of BCI, the studies from Mason and Birch [2003] and Mason *et al.* [2005] are closely related to the scope of our work. In the model presented by Mason and Birch [2003], which was derived using concepts from related fields such as HCI, the BCI system was described based on its functional components, and was employed as a base for constructing a framework and a taxonomy for BCI design. This model and taxonomy were later updated and expanded by Mason *et al.* [2005], using the Human Activity Assistive Technology model as base for its construction. Thus, this model considers BCI systems as an assistive technology, focusing on people with functional limitations that uses these systems to overcome an ability gap and perform an action in the environment.

More recently, Kosmyna and Lécuyer [2019] presented a conceptual space for EEG-based BCI systems. The authors described key concepts of BCI systems and their possible values, divided into four axes with nine sub-axes. These axes represent information about *when* the BCI system is used (i.e., the temporal features of the BCI system, such as whether its commands are employed actively or passively by the user); for *what* it is used (its application and employed neural mechanism); *how* it is used (multi-modal aspects of the system); and *where* it is used (virtual, physical or mixed environments). The authors demonstrate their conceptual space by instantiating a set of BCI-based systems from the literature, and found that most systems are based on virtual environments, using event-related (de)synchronization as neural paradigm, and are synchronous (the user must wait for a trigger to use a BCI command).

The functional model introduced by the IEEE P2731 working group is also a recent representational scheme for BCI systems, which divides the system into specialized functional modules, going from stages such as the data collection, transducer and control interface [Easttom, 2021]. The model is intended to serve as a base reference to unify the terminology of BCI systems, by means of representing the functioning of such systems in a general manner. The model itself is also based on the classical closed-loop scheme, and details each stage by means of describing the possible components of each module and their instantiation values. The model also includes the user as one of its components, and considers hybrid systems by representing other brain imaging methods in addition to EEG, and other physiological signals such as electromyography (EMG), electrooculography (EOG) and electrocardiography (ECG) as input modalities.

As stated in Section 1, BCIs are usually (but not exclusively) employed in serious games, given the intersection of contexts and applications for both fields. Models and classification schemes for serious games are presented, for example, in the works of Djaouti *et al*. [2011] and Lope and Medina-Medina [2017], which present taxonomic schemes for representing and classifying serious games, while McCallum and Boletsis [2013] present a classification scheme for the specific case of serious games for dementia. Considering both fields, there are also studies that focus on representing BCI-based serious games. Sung *et al*. [2012], for example, present a methodology and development architecture for creating new EEG-based serious games, which define roles for experts, game developers and designers in the development process and unify methodologies from both fields.

Although these models can represent a wide variety of BCI-based systems and their related concepts, to our knowledge there are currently no models for representing the case of EEG-controlled games. The BCI models presented in the literature can represent systems in a general manner and as a special case of assistive devices. However, specific components related to the game part of the system may be lost in this context. In the same sense, models for representing games, both general and specific, are not able to represent the components related to the capturing, processing and application of EEG signals from the user to the game. As detailed in Section 1, the definition of a specific model for the field could provide a standardized framework for representing EEG-based games, thus facilitating the comparison of different implementations, studies that employ them, and guide the development of new BCI games.

In this context, the model proposed in this work draws inspiration from related works of both fields, and was developed to close the gap between BCI and game systems by representing both as only one entity. The terminology defined in more general schemes was adapted to the context of both BCI and games. Our proposed model is also integrated in the sense that it integrates both structure and function in each of its components, allowing it to be used, for example, as an initial frame of reference for the system architecture of new EEG-based games. It is also unified, in the sense of unifying concepts, components and definitions of schemes from both BCI and games into a single theoretical model.

The proposed model expands upon the concepts presented in previous frameworks by integrating the neural, interactive and technical aspects of EEG-controlled games into a unified scheme. The general framework proposed by Mason and Birch [2003] and its later revision by Mason *et al*. [2005], although provides a model for describing the operational flow of BCI systems, are primarily oriented toward assistive and rehabilitation contexts, and do not explicitly address entertainment-based applications such as games. The conceptual space introduced by Kosmyna and Lécuyer [2019] defines a set of dimensions for describing EEG-based BCIs according to various aspects, serving as a descriptive, comparative and taxonomic tool, but does not consider the integration between aspects related to game-specific applications, such as gameplay mechanics and their corresponding neural control signals. Likewise, the IEEE P2731 model [Easttom, 2021] focuses on standardizing terminology and functional modules of BCI systems, but abstracts contextual aspects of their applications, such as in the context of entertainment and/or game environments.

In comparison to existing frameworks, the proposed model extends the classical closed-loop BCI architecture by incorporating, in addition to the more general EEG acquisition and processing components, elements related to game logic, control mechanics, and feedback interfaces. This integration provides a more complete and specialized representation of EEG-controlled games, allowing for their description, comparison and design within a single conceptual and functional model.

3 The MEG21 model for EEG-controlled games

In this section, the proposed general model for EEG-controlled games is presented, including its development process and how its final version was derived. We start by considering the principles that were considered for constructing the model, as they were the base for its initial derivation and current structure. Then, we detail the development process and the method for deriving its initial version, followed by the iterative process of refinement for its final version. Each final component is then described in sequence.

Our main goal was to construct an integrated model, in the sense of joining both function and structure of BCI and game components into a single scheme. This allows to consider not only the commonly employed architecture of those systems, in the sense of abstract and concrete implementation, but also the functions that these components perform in the system and the relation between then, including processing and transmission of input data, and the responses that each component produces for the following as output after transformation.

For presenting this model, we start by describing the principles and theoretical foundation for its construction, followed by its derivation process. We then detail this process and describe each component individually. As the model is also unified, considering that it unifies concepts and definitions from various sources from the fields of BCI and Games, we also present a list of sample studies that were employed both for defining, refining and/or specializing the model's components.

3.1 Foundation and principles

The main methodological background for construction the proposed model came from the fields of BCI and Games. As the model is intended to represent EEG-controlled games, theoretical knowledge from classic BCI works (e.g., Mason and Birch [2003]; Mason *et al*. [2005]; Wolpaw *et al*. [2002]) and the analysis of various BCI games from the literature (e.g., Bos *et al*. [2010]; Kaplan *et al*. [2013]; Kerous *et al*. [2018]; Marshall *et al*. [2013]; Ferreia *et al*. [2012]; Ferreira *et al*. [2014]), in addition to previous experience on both the development, evaluation of such games and their employment in controlled empirical experiments [Vasiljevic *et al.*, 2018a,b; Vasiljevic and de Miranda, 2019b,a, 2024b], served as the foundation for constructing and refining the model. More specifically, in addition to the theoretical and related studies, we started by analysing 82 games based on consumer-grade devices, which were gathered from 87 studies from over 800 articles [Vasiljevic and de Miranda, 2020a]. We later expanded this analysis to include BCI systems and games in a more general sense, including BCI games based on non-consumer-grade EEG devices, with over 600 studies analysed for possible games (not considering studies that employed games for EEG analysis, but that were not directly controlled by the EEG signals). A sample collection of these games and other secondary studies that were employed for defining and refining the model, as well as the methods for searching and selecting these sources, is provided next.

With the aim of being as general as possible, the model was constructed for representing virtually any kind of game that is controlled in any aspect using EEG. The main principles (px) that guided the construction of the model were that:

p1. The BCI system and the game system should be as less dissociated as possible;
p2. The model should be general enough to represent as best as possible any EEG-controlled game currently available in the literature; and
p3. The model should be expandable and adaptable for specific situations and contexts.

These main principles were based on the proposed Research Questions and their goals, as described in Section 1. For deriving the current version of the model, we start by considering a more abstract functional architecture for BCI-based systems. Then, we simplify this architecture to the point where it can be used for representing the specific case of EEG-controlled games in the most general sense. Then, we apply a reverse process of detailing this simplified architecture in incremental steps, considering both structural and functional components obtained from EEG-based games and other theoretical literature works from the fields of BCI and games, and iterate this construction until all relevant components are described.

More specifically, in this last stage, the model was refined in an iterative, incremental process consisted mainly of fitting games obtained from the literature in its components, and thus identifying missing, important components that could help describing those games more accurately. This process is illustrated in Fig. 1[1], while the logic that guided its derivation is described in the following subsection.

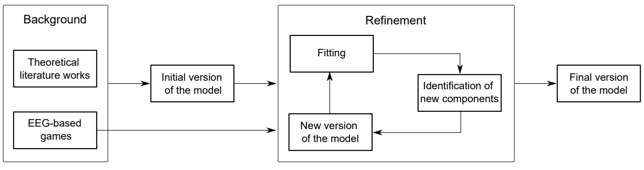

Figure 1. Development process of the model.

[1]All figures presented in this work are vectorial. This means that they can be enlarged by the reader as required without loss of resolution.

3.2 Model derivation and construction

The model itself is based on the closed-loop neurofeedback scheme for BCI-based systems (Fig. 2). In this scheme, the BCI system is de-composed into six main steps representing its function: data acquisition, pre-processing, feature extraction, feature classification/translation, application, and (neuro)feedback [Wolpaw *et al.*, 2002]. This scheme is largely seen in a number of studies, in which the BCI system architecture is based or adapted from it (e.g., Hasan and Gan [2012], Koo *et al.* [2015], Lalor *et al.* [2005], and Tangermann *et al.* [2008]), and resembles other BCI-based models, such as the functional models of Mason and Birch [2003] and of the IEEE P2731 working group [Easttom, 2021].

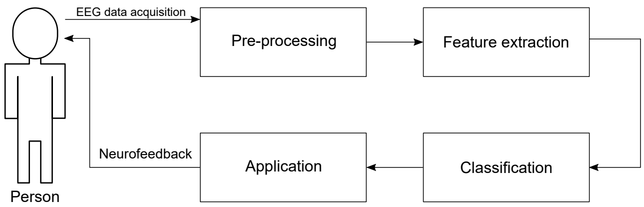

Figure 2. Classic closed-loop neurofeedback architecture.

In a general sense, the classic BCI system can be seen as a filter (or transducer), receiving and transforming an input signal (the EEG data from the user) into an output control signal (for the application to consume). The target application then feeds the results of this control signal back to the user, which in turn consciously or unconsciously alters his/her brain electrochemical dynamics in response, and this change is then captured by the EEG acquisition device, composing the closed-loop architecture. Thus, the classic BCI closed-loop architecture scheme from Fig. 2 can be simplified into the following model (3):

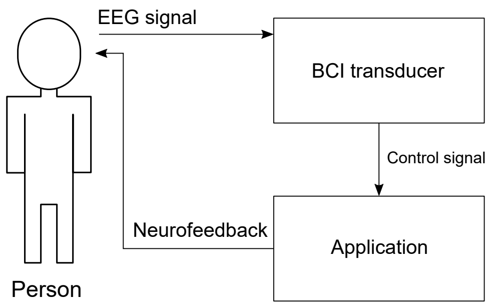

Figure 3. Simplified closed-loop neurofeedback model.

In the proposed model and in the context of games, the target application is the game itself, being directly or indirectly controlled by the control signal provided by the BCI transducer. The model is derived by an even more simplified scheme (Fig. 4), in which the game and the BCI transducer are seen as only one entity (based on principle p1 of the model, as described in Section 3.1): the EEG-controlled game, which receives an input from the player, and provides a feedback based on its current internal state.

It is important to notice that, in this simplified scheme, the input is not restricted to an EEG signal, nor is the feedback restricted to a neurofeedback itself. The reason is that, in the context of games, the application can be controlled not only by the EEG signals, but by other forms of controls as well,

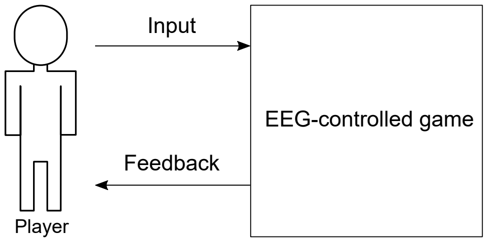

Figure 4. Simplified EEG-controlled game model.

such as physical ones (e.g., mouse, keyboard, joysticks, and gamepads), non-physiological ones (e.g., voice, eye movements, and gestures) or other physiological ones (e.g., heart rate, muscle activity, breathing rate, and electrodermal activity)[2]. In the same context, the feedback provided by the game can not only represent the response to the EEG-based control, but it can also represent the changes in the game world (and in the objects contained in this world) that were caused both internally by game itself, and externally by the physical and/or physiological controls from the player(s).

These details are fundamental for the detailing of the model. Every component of the simplified model can be further decomposed into several parts: The input is composed of the EEG input and other physical/physiological inputs; the feedback is composed of both the feedback from the game's virtual interface and/or the neurofeedback; and the EEG-controlled game is an implementation that contains the game logic, including the control mechanics and the game world, and an interface to receive the input(s) and to provide feedback to the player. This more detailed model is represented in Fig. 5.

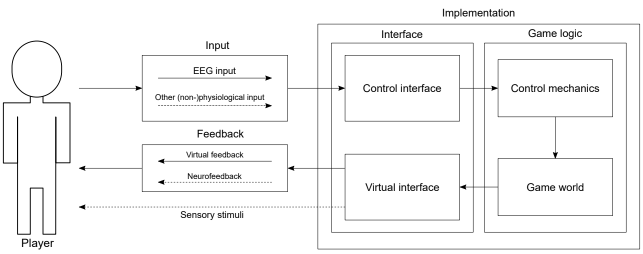

Figure 5. Detailed EEG-controlled game model (dashed lines represent optional elements).

In this model, the optional components are marked with non-continuous lines. The presence of optional components contributes for a more adaptive scheme (based on principle p3 of the model, as described in Section 3.1). Here, the other physical and physiological inputs are optional, as the model represents and focus on EEG-controlled games. The control interface receives the input and translates it into control signals, which are employed as control mechanics in the game logic to alter the game world. This change in the game world reflects on the virtual interface, which presents its state to the player in the form of a feedback. This feedback can be visual, auditory or somatosensory (haptic/vibrotactile or thermal).

Although the virtual feedback is always present, as it represents the game environment and the status of the game to the player (assuming that a player cannot play a game without knowing at least its status in a finite amount of time), the neurofeedback is optional, as the game can be played using a passive BCI (e.g., passively adjusting the game difficulty using the player's emotions), and thus no neurofeedback is explicitly provided. The sensory stimuli is another optional element which was introduced based on both principles p2 and p3 of the model (as described in Section 3.1), as specific control signals (e.g., SSVEP[3] and P300[4]) require an external stimulus to be generated and recorded by the EEG device.

Finally, the detailed model presented in Fig. 5 can be further detailed to represent all components of an EEG-controlled game. This allow for the instantiation of each of these components in a very specific sense, as opposed to a more abstract model. This complete general model can be seen in Fig. 6. For this expansion, both the BCI and non-BCI inputs are detailed and captured by the corresponding control interface. The game world is also detailed based on the definitions of games as a collection of game objects inserted in a game environment, in which playable and non-playable characters interact with. The feedback is also detailed to include sensory modalities and the separation of BCI and non-BCI feedbacks. Each of these components are detailed next and their description are summarized in Table 1.

In the complete model, the EEG input is captured in the data collection step by **sensors** connected to an **EEG device**, which transfers the acquired EEG data to the BCI module in the **control interface** for the processing of this data. This include the classic steps in a BCI system, that is, pre-processing, feature extraction, classification, and sending the classified control signal to the application (i.e., the game).

In regression tasks, where there is no need for a classifier and the system translates the signal's extracted features directly into a continuous variable to be employed by the game (e.g., applying the theta/beta ratio to calculate the players' level of attention, or alpha levels to estimate the player's level of relaxation), the module transmits the processed feature translation directly to the game after the feature extraction step. There can also be an intermediate, optional step for feature selection before the actual classification, usually employed to increase the classifier's accuracy.

The received **control signals** are then employed as **control mechanics** in the game logic, altering the **game world** and its components, that is, the **game environment**, and eventual player characters, game objects, and Non-Playable Characters (NPCs). Every component in the game world, with exception of the game environment, are optional, as a game can be designed with or without objects and characters, but not without an environment in which the game logic occurs and that the player can interact with it in any manner. If exists, the **player character** can interact with both the environment and its objects and with other non-playable, computer-controlled characters, or even with other player characters, in the case of multiplayer games. The **NPCs**, while being agents, can perceive and/or perform actions in the environment.

In the same sense, the other **physiological and non-physiological** data, labelled as "Non-BCI" for a more general

[2]This is also the reason that the game component is referred as "EEG-controlled" rather than "EEG-based" in this work, as the first term is a generalization of the latter, that is, it can represent any game that is controlled by EEG, including those that are based solely on this kind of control.

[3]Steady-state visually evoked potential. A potential that is evoked when a visual stimulus, such as a blinking light, is presented at a steady rate.

[4]A positive potential that is evoked approximately 300 ms after an oddball stimulus.

term, are handled by their own modules and control their own mechanics within the game logic. They are also optional components, given that the game can be designed to be controlled solely with EEG controls. All these changes, performed by the player or by the game itself, are then updated in the game's **virtual interface**, which is composed by the game world interface, the neurofeedback interface, and the stimuli generator.

The **game world interface** is used to represent all components of the game world, including the player character and the NPCs. This interface can contain the neurofeedback interface and the stimuli generator, or these components can be separated, having their own interfaces (e.g., the stimuli generator or the neurofeedback can be contained in a separate screen or a device connected to the subject's body). While the game world interface and the **neurofeedback interface** provide feedback for the player, the **stimuli generator** provides a sensory stimulus, in accordance with the previously presented model in Fig. 5. There is also a representation for **storage**, since data from the EEG and non-EEG signals, their processing, and game events may be stored for use in online playing or offline analyses.

3.3 Component sources

As aforementioned, several sources from primary and secondary studies were employed for both the initial version of the model and for refining it to its current version. Table 2 presents a group of these sources and the components that were defined, refined or specialized based on them, including whether the component was proposed by unifying concepts that are related to both BCI and games. Sources employed for defining components were mostly employed in the derivation and construction of the initial version of the model. Sources employed for refining the model were employed in the interactive refinement cycle as shown in Figure 1, while sources employed for specializing were employed in latter stages of refinement or demonstration.

We sampled sources from all of these stages of construction and refinement for composing Table 2. For **defining** components, we listed several characteristics that were conceptualized or reported in secondary and primary studies. For **refining**, we further joined similar concepts in broader categories or divided into more specific components. We later **specialized** the components by considering how they could be described using common and recurring classification values found in primary and secondary studies, further refining the model to its current state. Note that some sources are not from the context of games, even when helping in defining game-related components (e.g., BCI control mechanics within the game, abstracted from the control for a general application). Also, due to the iterative nature of the refinement process, the same source could be employed for defining, refining or specializing different components of the model.

The selection of studies to base the construction of the model was performed in two parts. First, we employed all studies that were analysed from our previous systematic literature review on games using consumer-grade EEG devices [Vasiljevic and de Miranda, 2020a] and its related works. As

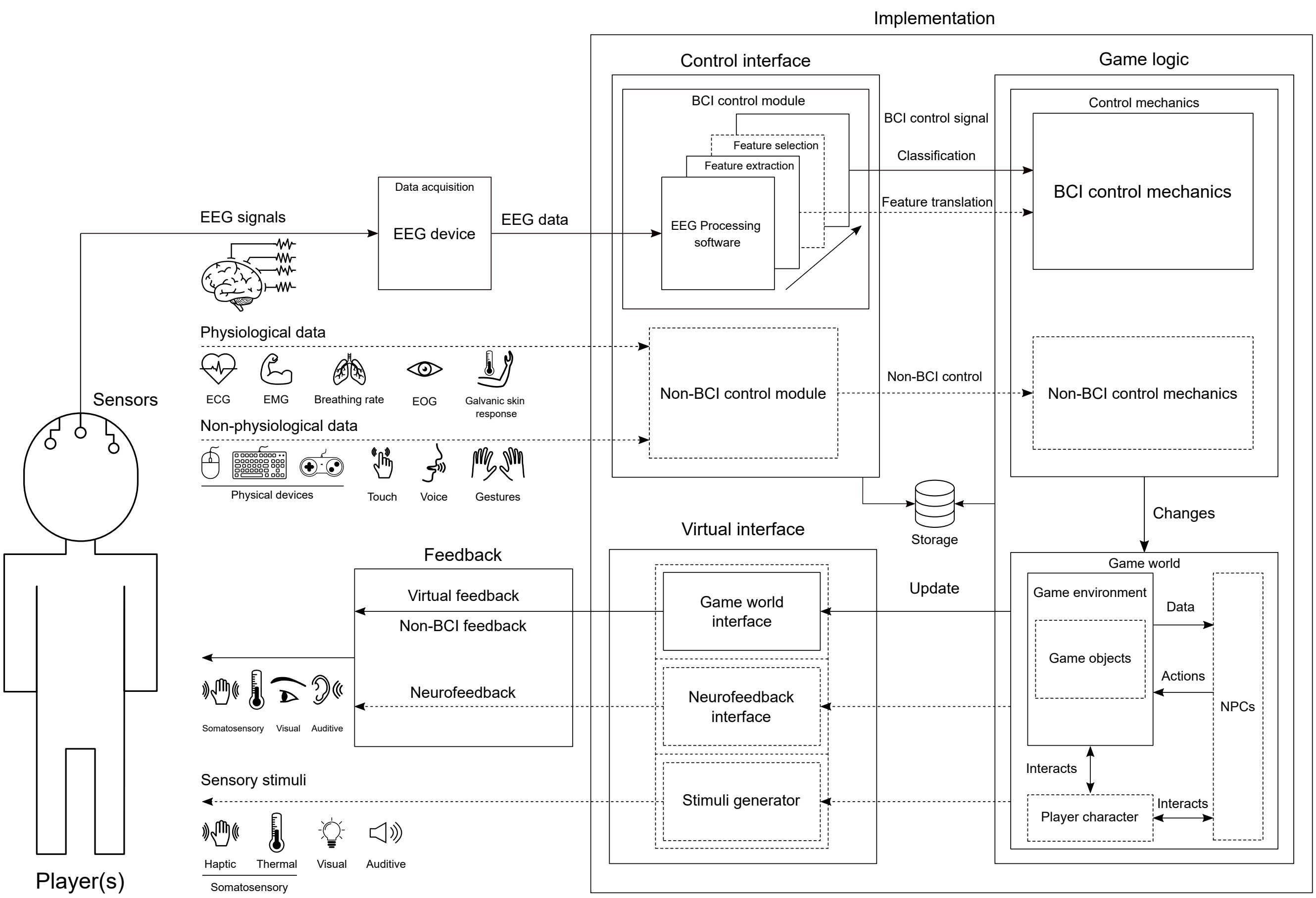

Figure 6. Complete general EEG-controlled BCI game model (continuous lines represent mandatory elements, while dashed lines and components are optional).

described in Section 3.1, these included 82 games from 87 primary studies. As these studies are restricted to the scope of consumer-grade devices, we later perfomed another structured search in major scientific databases, including Scopus, Web of Science, and Google Scholar. As with the systematic review, the search strategy combined terms related to the field of BCI (i.e., BCI, brain-computer interface, brain-machine interface, BMI, EEG, electroencephalogram, mind-controlled, brain-controlled, neurofeedback, and biofeedback) and application context (i.e., game, entertainment, gaming, and videogame), but without terms that would filter technology (for consumer-grade devices) or time, as was with the systematic review.

Studies were included if they (i) explicitly employed EEG signals as part of the interaction or adaptation mechanisms of a game, (ii) provided sufficient methodological detail to identify their components, and (iii) were written in English, Portuguese, or Spanish. Exclusion criteria comprised review papers, studies without EEG integration (or that would use EEG for monitoring only, rather that actively or passively controlling the game), and works focusing solely on invasive recordings. The retrieved works were screened manually, and non-excluded works were used for either defining, refining or specializing components in an iterative manner, as described in Section 3.1.

Since the goal of this step was not to conduct a review but to construct a model with a sufficiently large base as its foundation, secondary studies that were found during the searches, including reviews, taxonomies, models, frameworks and conceptual spaces were also analysed in both fields (BCI and games) for possible definitions and components that could be employed in the initial version of the model. The most relevant of these studies are listed and described in Section 2, as well as how they are compared to our proposed model. As such, they are also listed in Table 2.

3.4 Ethical considerations

The use of BCI systems in gaming environments introduces a set of ethical concerns that should be considered during de-

Table 1. All model's components and their description.

Component		Description
EEG data collection	**Sensors**	The type and amount of sensors that were employed to capture the player's EEG data. In the case of EEG, active or passive electrodes are usually employed. These electrodes can be wet (i.e., they require a saline or conductive substance to help lowering the impedance) or dry, and are generally placed strategically on the scalp depending on the neural mechanism that the researcher intends to identify.
	EEG device	The biosignal amplifier and/or head-mounted device that was employed to receive the EEG data from the sensors. The captured data is usually amplified and pre-processed before being used by the feature extraction and/or classification algorithm. Depending on the device (e.g., consumer-grade EEG devices), the device can also perform the pre-processing and feature extraction/classification steps.
Control interface	**BCI control signal**	The EEG-based control signal or underlying neural mechanism that was employed as a control command to the game. Examples of these control signals are the SSVEP, P300, motor imagery, and cognitive states, such as attention, relaxation and emotions.
	Non-BCI control	Any other non-BCI control, such as physical/analogical/digital controls (e.g., mouse, keyboard, joystick) and other biophysical signals.
Control mechanics	**BCI**	How the EEG-based control is employed to change or to interact with the game world. This include moving or acting with a game character, interacting with objects and/or non-playable characters from the game world or altering the game environment.
	Non-BCI	Similar to the BCI control mechanics, but applied to other, non-BCI controls, if they exist.
Game world	The game world is composed of its environment, and eventual player characters, non-playable characters (NPCs) and game objects. Depending on the game rules, the player can act through a player character or directly to the game and its objects.	
	Player(s) character(s)	The players' controllable characters in the game world (if it exists), including its amount (single player, multiplayer), and how the player interacts or controls it.
	Environment	The environment that the game takes place. This environment can be virtual (i.e., in a virtual, simulated world) or physical (i.e., in the real world, using physical objects or machines).
Virtual interface	The virtual interface is responsible for providing the player(s) with feedback from the game, as well as external stimuli and neurofeedback. This include the game world interface, responsible for the virtual feedback that updates the player about the status of the game world; the neurofeedback interface; and the stimuli generator. Note that the latter two can both be included in the game world interface, or be separated (e.g., an external device used to generate visual or auditory stimuli that is separated from the game screen).	
	Neurofeedback (NF) interface	Provides the specific feedback that updates the player about his/her internal mental state and/or regarding the result of the signal processing algorithm. This can be, for example, a numerical value, a change in the virtual interface (e.g., an interface element that visually changes according to the classification result, or the movement of an object/character in the game world), a sound, a vibration etc. Note that this feedback may also be embedded in the virtual feedback.
	Stimuli generator	Generates external stimuli to evoke specific brain responses, which are required for exogenous control signals (e.g., P300 and SSVEP). These stimuli can be visual, auditive or somatosensory (e.g., thermal and vibrotactile).

sign, development, evaluation and employment of these games in clinical, research and entertainment contexts. These involve ethical aspects related to collecting and processing neural data (as in the *EEG Data Collection* component), adapting gameplay based on inferred cognitive or emotional states and other mental processes, such as motor or speech imagery (as in the *Control Interface* and *Control Mechanics* components), and providing neurofeedback to players (as in the *Virtual Interface* component). As such, explicitly addressing these ethical concerns is should be a priority for researchers and developers for guiding the responsible application of such technologies in interactive and entertainment systems, especially for clinical and/or empirical research.

The acquisition of EEG data raises unique ethical challenges due to the inherently sensitive nature of neural information. Unlike other physiological signals, data from the brain can be more directly decoded for inferring aspects of cognitive states, such as attention, and emotional content, such as feelings of anger, fear or sadness. Ethical implications include the risk of privacy violation, such as the use of recordings for purposes not originally consented to, and potential inference of sensitive states [Sun and Ye, 2023]. It is possible, for example, to infer whether a player is feeling anxious or stressed, or whether they showed increased attention or interest for a given visual stimulus or scene, which can cause embarassment for the player. In a more general sense, this data could also be used for discrimination, for example, neural signatures showing a predisposition for neurological conditions, such as dementia [Ienca *et al.*, 2022], especially given the possibility of false positive or negative results.

To address these concerns, developers and researchers should adopt data minimization (collect or store only what is necessary) and anonymization practices. This is particularly important in the context of studies using EEG-based signals with public repositories or open access to their data, regardless of the application domain of games, since one could link these sensitive information to specific individuals [Ienca *et al.*, 2022]. It is also important to apply informed consent procedures specifying how EEG data (or other physiological modalities) will be processed and stored, and communication with players about the scope and limits of the use of their neurological or physiological data in general. These recommendations align with recent governance frameworks for brain data that emphasize mental privacy protection and ethical employment of EEG data in interactive applications, especially considering recent international regulations [Ienca *et al.*, 2022; Ienca and Malgieri, 2022].

BCI controls and dynamic adjustment mechanics in games introduce further ethical considerations because they directly link players' cognitive or emotional states to in-game outcomes, which is also related to the aforementioned concerns regarding risks of privacy violations. In addition, systems that adapt gameplay based on cognitive states influence the player experience in ways that may not be fully transparent or controllable by the user. For example, users could not feel in control of a game based on EEG signals, even if their performance in said game is positive [Vasiljevic and de Miranda, 2019b]. This raises issues of autonomy, agency and explainability [Sun and Ye, 2023], that is, players should be aware of how their brain signals influence game behaviour and have control over which adaptations occur.

The game design, in this context, should include feedback to users about how their brain signals affect game mechanics, and opt-in or opt-out controls for adaptive features [Sun and Ye, 2023]. This is specially important for passive controls, such as changing difficulty or game scenarios base on players' emotions, as the mechanic itself may depend on the user not focusing on that particular mental process.

Finally, while neurofeedback can support cognitive training and therapeutic applications through self-regulation, it may also overstate the accuracy of inferred states when used in entertainment or non-clinical contexts. Ethical issues therefore include ensuring that feedback is accurate, beneficial and non-manipulative, and that users clearly understand the limitations of possible neurofeedback effects [Livanis *et al.*, 2024]. This is particularly relevant when games provide real-time adaptive responses based on inferred mental states such as attention or relaxation, where incorrect feedback may cause frustration, misinterpretation of brain activity or unrealistic expectations about mental control [Gordon and Seth, 2024; Livanis *et al.*, 2024]. In this sense, game developers and researchers should employ validated neurofeedback controls (or aligned with specific hypothesis about their effects, if possible) and explicit their limitations.

4 Model demonstration

The method to demonstrate the model is similar to the approaches employed by Mason and Birch [2003] and Kosmyna and Lécuyer [2019], by means of demonstrating its usefulness through the representation of a set of works that describes EEG-based systems/games using the model, and instantiating each of its components. Tables 3, 4 and 5 present the result of this demonstration, with games listed in alphabetical order.

Games were selected from studies using different game genres, control styles and EEG-based control signals to provide more diversity in the data. All positions in the *Sensors* subcomponent are based on the 10-20 international system and its extended versions. Optional values that were not present in the game were marked as "N/A" (not applied). Similar classification values may have slightly different descriptions, for illustrating different ways of objectively classifying instances.

4.1 Summary and category values

As can be seen from Tables 3 to 5, some characteristics of the games can be described with recurring, commonly applied values. These values can be summarized according to each component, allowing for subdividing them based on general categories, briefly described in Table 1, and refined through the demonstration. Each of these recurring categories will be presented and detailed next, grouped by the components of the model. These values also help in defining other details in the description that may be relevant in specific contexts, which were omitted in the demonstration for providing a less implementation-specific description of the BCI game system.

4.1.1 *EEG Data Collection*

An objective description of the *Sensors* component would include their type, number and location. Although this location is usually described by means of the standard 10-20 System

Table 2. Sample collection of sources (in alphabetical order by author) that served as base for defining (■), refining (▲) or specializing (◆) the model's components. Not all sources provide new or updated information in a given stage of definition or refinement (□).

	EEG data collection		Control interface		Control mechanics		Game world		Virtual interface	
Source	**Sensors**	**EEG device**	**BCI control**	**Non-BCI control**	**BCI**	**Non-BCI**	**Player(s) character(s)**	**Environment**	**NF interface**	**Stimuli generator**
Abdessalem and Frasson [2017]	■	■	■	■	■	■	■	■	□	□
AbuRas *et al*. [2018]	◆	◆	◆	◆	◆	◆	◆	◆	◆	□
Ahn *et al*. [2014]	■	■	■	□	■	□	□	□	□	■
Ali and Puthusserypady [2015]	▲	▲	▲	□	▲	□	◆	▲	▲	▲
Alchalabi *et al*. [2018]	▲	▲	▲	▲	▲	▲	▲	▲	▲	□
Amini and Shalchyan [2023]	◆	◆	▲	□	▲	□	◆	◆	◆	▲
An *et al*. [2016]	◆	◆	◆	□	◆	□	◆	◆	◆	□
Antle *et al*. [2018a]	■	■	■	■	■	■	■	■	■	□
Antle *et al*. [2018b]	▲	▲	▲	▲	▲	▲	■	■	■	□
Arrambide *et al*. [2019]	◆	◆	◆	◆	▲	◆	◆	◆	◆	□
Beveridge *et al*. [2016a]	◆	◆	◆	□	◆	□	◆	◆	◆	◆
Beveridge *et al*. [2016b]	◆	◆	◆	□	◆	□	◆	◆	◆	◆
Blandón *et al*. [2016]	◆	◆	◆	◆	◆	◆	◆	◆	◆	□
Bonnet *et al*. [2013]	◆	◆	◆	□	◆	□	◆	◆	■	□
Bos *et al*. [2010]	■	□	■	■	■	■	■	■	■	■
Chen *et al*. [2017a]	◆	◆	◆	◆	◆	◆	◆	◆	◆	□
Chen *et al*. [2017b]	◆	◆	◆	□	◆	□	◆	◆	◆	◆
Choi *et al*. [2017]	□	□	■	■	■	■	■	■	■	■
Coogan and He [2018]	▲	▲	▲	□	▲	□	□	▲	▲	□
Cruz *et al*. [2018]	▲	▲	▲	□	▲	□	▲	▲	▲	▲
Easttom [2021]	◆	◆	◆	◆	□	□	□	□	◆	◆
Fernandez *et al*. [2016]	▲	▲	▲	▲	▲	▲	▲	▲	▲	□
Ferreira *et al*. [2013]	■	■	■	■	■	□	■	■	■	■
Ferreira *et al*. [2014]	□	■	■	■	■	■	□	■	■	■
Finke *et al*. [2009]	▲	▲	▲	□	◆	□	◆	◆	◆	▲
Gurkok *et al*. [2016]	□	□	■	■	■	■	□	■	□	□
Hasan and Gan [2012]	▲	▲	▲	□	▲	□	◆	▲	▲	▲
Heintz and Law [2015]	□	□	□	■	■	■	■	■	□	□
Henrik *et al*. [2011]	□	▲	▲	■	▲	■	▲	▲	▲	□
Hjorungdal *et al*. [2016]	◆	◆	◆	◆	◆	◆	◆	◆	◆	□
Hong and Khan [2017]	■	■	■	□	■	□	□	■	■	■
Horie and Nawa [2017]	◆	◆	◆	▲	◆	▲	▲	◆	◆	□
Israsena *et al*. [2015]	▲	▲	▲	▲	▲	▲	▲	▲	▲	□
Joselli *et al*. [2014]	■	■	■	■	■	■	□	■	■	□
Kaplan *et al*. [2013]	□	□	■	□	■	□	■	■	■	■
Kerous *et al*. [2018]	■	■	■	■	■	■	■	■	■	■
Koo *et al*. [2015]	▲	▲	▲	□	▲	□	□	▲	▲	▲
Kosmyna and Lécuyer [2019]	■	■	■	■	■	□	□	■	■	■
van de Laar *et al*. [2013]	▲	▲	▲	▲	▲	▲	■	▲	▲	□
Laamarti *et al*. [2014]	□	□	□	■	■	■	■	■	□	□
Lalor *et al*. [2005]	▲	▲	▲	□	▲	□	■	■	▲	▲
Lance *et al*. [2016]	□	□	■	□	■	■	□	■	■	■
Leeb *et al*. [2013]	▲	▲	▲	◆	◆	◆	◆	▲	▲	□
Leite *et al*. [2018]	▲	▲	▲	□	▲	□	□	▲	▲	▲
Li *et al*. [2016]	▲	▲	▲	□	▲	□	□	▲	▲	□
Li *et al*. [2017]	▲	▲	▲	□	▲	□	□	▲	▲	□
Li *et al*. [2021]	◆	◆	◆	□	◆	□	◆	◆	◆	◆
Lim and Ku [2018]	◆	◆	◆	□	◆	□	□	◆	◆	◆
Liu *et al*. [2016]	▲	▲	▲	▲	▲	▲	▲	▲	▲	□
Lope and Medina-Medina [2017]	□	□	□	■	■	■	■	■	□	□
Maby *et al*. [2012]	▲	▲	▲	□	▲	□	◆	▲	▲	▲
Marshall *et al*. [2013]	■	■	■	□	■	□	■	■	■	■
Mason and Birch [2003]	■	■	■	■	■	■	■	■	■	■
Mason *et al*. [2005]	■	■	■	■	■	■	■	■	■	■
McMahon and Schukat [2018]	◆	◆	◆	□	◆	□	□	◆	◆	□
Mehta *et al*. [2010]	◆	◆	◆	□	◆	□	◆	◆	◆	◆
Mühl *et al*. [2010]	▲	▲	▲	▲	▲	▲	▲	▲	▲	▲
Muñoz *et al*. [2016]	◆	◆	◆	◆	▲	▲	▲	◆	◆	□
Murphy *et al*. [2018]	◆	◆	◆	◆	◆	◆	□	◆	◆	□
Nicolas-Alonso and Gomez-Gil [2012]	■	■	■	■	□	□	□	■	□	■
Nijholt *et al*. [2009]	■	■	■	■	■	■	■	■	■	■
Obbink *et al*. [2012]	▲	▲	▲	▲	▲	▲	◆	◆	▲	▲
Ochi *et al*. [2017]	◆	◆	◆	◆	◆	◆	◆	◆	◆	□
van der Pal *et al*. [2018]	▲	▲	▲	▲	▲	▲	▲	▲	□	□
Parafita *et al*. [2013]	▲	▲	▲	□	▲	□	▲	▲	▲	■
Paszkiel *et al*. [2021]	◆	◆	◆	□	◆	□	◆	◆	▲	□
Prapas *et al*. [2023]	◆	◆	◆	□	◆	□	◆	◆	□	□
Putri *et al*. [2019]	◆	◆	◆	□	◆	□	◆	◆	◆	□
Ramadan and Vasilakos [2017]	■	■	■	□	□	□	□	■	■	■
Reinschluessel and Mandryk [2016]	▲	▲	▲	▲	▲	▲	▲	▲	▲	□
Scherer *et al*. [2016]	▲	▲	▲	□	▲	□	□	▲	▲	□
Schoneveld *et al*. [2016]	▲	▲	▲	▲	▲	▲	▲	▲	▲	□
Serrano-Barroso *et al*. [2021]	◆	◆	◆	□	◆	□	◆	◆	◆	□
Škola and Liarokapis [2018]	▲	▲	▲	□	▲	□	▲	▲	▲	□
Song *et al*. [2017]	◆	◆	◆	◆	◆	◆	◆	◆	□	□
Sourina *et al*. [2011]	▲	▲	▲	□	▲	□	▲	▲	▲	□
Stein *et al*. [2018]	▲	▲	▲	■	▲	■	▲	▲	■	□
Tangermann *et al*. [2008]	□	□	◆	□	▲	□	◆	◆	▲	□
Vasiljevic *et al*. [2018a]	■	■	■	□	■	□	■	■	■	□
Vasiljevic *et al*. [2018b]	■	■	■	□	■	□	■	■	■	□
Vasiljevic and de Miranda [2020a]	■	■	■	■	■	■	□	■	■	■
van Vliet *et al*. [2012]	▲	▲	▲	□	▲	□	◆	▲	▲	▲
Vourvopoulos *et al*. [2016]	▲	▲	▲	□	▲	□	□	▲	▲	□
Wang *et al*. [2019]	■	■	■	■	■	□	□	■	■	■
Wolpaw *et al*. [2002]	■	■	■	■	■	■	□	■	■	■
Yeh *et al*. [2018]	▲	▲	▲	□	▲	□	▲	▲	▲	□
Zhou *et al*. [2017]	◆	◆	◆	□	◆	□	◆	◆	□	□

Table 3. Demonstration of the model and its components.

	αWoW [van de Laar *et al.*, 2013]	
EEG data collection	**Sensors:**	Four wet electrodes, placed at positions P1, P2, CP7, and CP8.
	EEG device:	An Emotiv Epoc.
Control interface	**BCI control:**	Relaxation level, calculated using a FFT of the α frequency band.
	Non-BCI control:	Mouse and keyboard.
Control mechanics	**BCI:**	Activates a specific ability that the player can cast to change the shape and powers of its avatar.
	Non-BCI:	Controls the movement of the character and the casting of abilities.
Game world	**Player character:**	The player controls a humanoid avatar that can shape-shift into a bear, and interacts with multiple other players, each with their own avatars, usually humanoid.
	Environment:	Virtual, three-dimensional, massive multiplayer and online open world.
Virtual interface	**World interface:**	PC monitor display, with a three-dimensional view of the world and third-person view of the player character.
	NF interface:	Embedded in the game's graphical interface. A bar with a numerical threshold value that indicates whether the player reached the required cognitive state to activate the related ability.
	Stimuli generator:	N/A.
	Aiming Game [Henrik *et al.*, 2011]	
EEG data collection	**Sensors:**	Not informed (up to 14 saline electrodes, given the employed device).
	EEG device:	An Emotiv Epoc.
Control interface	**BCI control:**	Emotion (arousal), represented with a value ranging from 1 to 5.
	Non-BCI control:	Mouse.
Control mechanics	**BCI:**	Dynamically adjusts the game difficulty, distorting the aim and blurring targets.
	Non-BCI:	Used to point and click the target airplanes in the screen.
Game world	**Player character:**	A single player with no in-game avatar.
	Environment:	A virtual, 2-dimensional picture of the sky, with moving targets.
Virtual interface	**World interface:**	A PC monitor screen, showing the virtual environment and the player's aim.
	NF interface:	A bar, divided into five segments, shows the player's current level of arousal.
	Stimuli generator:	N/A.
	AmbuRun [Abdessalem and Frasson, 2017]	
EEG data collection	**Sensors:**	Up to 14 saline electrodes.
	EEG device:	An Emotiv Epoc.
Control interface	**BCI control:**	Emotion recognition, specifically, frustration and excitement.
	Non-BCI control:	An analogic, wireless gamepad with directional and action controls.
Control mechanics	**BCI:**	The passive recognition of emotions provide passive control of the speed of an ambulance and game difficulty (number of obstacles).
	Non-BCI:	The gamepad controls the movement direction of the players' avatar.
Game world	**Player character:**	A three-dimensional ambulance carrying a health patient.
	Environment:	An infinite road in a desert, with obstacles such as other cars and trucks.
Virtual interface	**World interface:**	A FOVE virtual reality headset, which shows the road and a third-person view from the top of the ambulance.
	NF interface:	N/A.
	Stimuli generator:	N/A.
	Bacteria Hunt [Mühl *et al.*, 2010]	
EEG data collection	**Sensors:**	34 active Ag/AgCl electrodes, positioned at sites Pz, Oz, O1, O2, and 30 others.
	EEG device:	A BioSemi ActiveTwo, sampling at 512 Hz.
Control interface	**BCI control:**	SSVEP and alpha band power. SSVEP is classified using a combination of power in harmonics of the target frequencies and threshold logic, while the final alpha band power is obtained after averaging and scaling values after a 512-point FFT.
	Non-BCI control:	Keyboard, using the arrows and Ctrl keys.
Control mechanics	**BCI:**	Alpha band power controls the speed of the targets, thus increasing or decreasing the game difficulty. SSVEP is employed to trigger the eating mechanics and gaining points.
	Non-BCI:	The arrow keys from the keyboard moves the player's character in the corresponding direction. In a non-BCI game match, the Ctrl key also serves to trigger an action in the game.
Game world	**Player character:**	A single player controls a two-dimensional representation of an amoeba.
	Environment:	A two-dimensional white environment with the player's avatar and targets, represented by images of bacteria scattered across the screen.
Virtual interface	**World interface:**	A computer screen showing a top-down view of the game world and its objects, along with classification results and player score.
	NF interface:	A graph representing a recent history of alpha band power and SSVEP classification, positioned at the top of the game screen.
	Stimuli generator:	When at a certain range of a target, the stimuli appears above it to elicit SSVEP responses.
	BrainArena [Bonnet *et al.*, 2013]	
EEG data collection	**Sensors:**	Two GAMMACaps with eight active electrodes positioned over the parietal region.
	EEG device:	Two g.USBAmp amplifiers.
Control interface	**BCI control:**	Motor imagery, classified using a LDA classifier with band power features extracted using CSP filters.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	The player must perform the indicated imagined movement to move a ball into the target goal.
	Non-BCI:	N/A.
Game world	**Player character:**	Two players, with no avatar to represent them in the game.
	Environment:	A black scenario with three feedback gauges, two goals, a ball and instructions for the current imagined movement to be performed by each player.
Virtual interface	**World interface:**	A PC monitor screen, showing all elements of the game world for both players.
	NF interface:	Three gauges in the game screen indicating the intensity of the recognized motor imagery command (left, right), one for each player and one for the cumulative result of the identified command.
	Stimuli generator:	N/A.
	Catching fruit game [Ali and Puthusserypady, 2015]	
EEG data collection	**Sensors:**	Three gold plated electrodes, placed at positions Oz, Fpz, and Fz or A1 for reference.
	EEG device:	A g.tec g.USBamp amplifier.
Control interface	**BCI control:**	SSVEP, classified using autocorrelation and threshold logic.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Focusing on the right or left stimulus moves the player's character to the corresponding direction.
	Non-BCI:	N/A.
Game world	**Player character:**	A two-dimensional, virtual ninja character holding a plate above its head, controlled by a single player.
	Environment:	A mix of two- and three-dimensional virtual environments, with a 3D classroom and a 2D game on the class board.
Virtual interface	**World interface:**	A computer screen, showing a frontal view of the 3D classroom with the 2D game on the background. A different view may be presented depending on the stage.
	NF interface:	The movement of the player avatar serves as feedback for the classified movement.
	Stimuli generator:	Two squares, embedded in the game screen, flickering between black and white at 7 and 9 Hz.
	Competitive balance game [Putri *et al.*, 2019]	
EEG data collection	**Sensors:**	2, 16 or 32 electrodes.
	EEG device:	A g.USBamp amplifier.
Control interface	**BCI control:**	Relative alpha power, measured as a percentage to the power of the 2–30 Hz frequency band.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Each player must maintain their relative alpha power at least 10% higher that the opponent's to balance the scale to their side.
	Non-BCI:	N/A.
Game world	**Player character:**	Two players, with no in-game avatar.
	Environment:	A virtual, 2D view of a seesaw representing the balance between each player's relative alpha power.
Virtual interface	**World interface:**	A PC monitor screen sharing the view of both players.
	NF interface:	Two vertical bars at the lateral of the central seesaw, showing the percentage of the relative alpha band of the corresponding player.
	Stimuli generator:	N/A.
	Connect Four [Maby *et al.*, 2012]	
EEG data collection	**Sensors:**	A 32-channel ActiCap system with nine silver chloride electrodes.
	EEG device:	A BrainAmp amplifier.
Control interface	**BCI control:**	P300, calculated with a bayesian classifier after spatial and temporal filtering.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Used to select a target column in a game of Connect Four with two players.
	Non-BCI:	N/A.
Game world	**Player character:**	The players have no avatar, but can be represented by their pieces, each with a different color.
	Environment:	A virtual, two-dimensional Connect Four game board.
Virtual interface	**World interface:**	PC monitor display showing the board and the time left to make a move.
	NF interface:	A rectangle appear over the selected column to indicate the classification result.
	Stimuli generator:	Each column of the game board flashes in sequence to evoke the P300 potential.
	GokEvolution [Serrano-Barroso *et al.*, 2021]	
EEG data collection	**Sensors:**	A single dry sensor at site Fp1.
	EEG device:	A NeuroSky MindWave device.
Control interface	**BCI control:**	Concentration level, measured using the NeuroSky's eSense metric.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Staying concentrated above a certain threshold for a given period of time increases the player's concentration gauge which, when full, makes the player's avatar evolve. The process is repeated until the final stage of evolution.
	Non-BCI:	N/A.
Game world	**Player character:**	A single player, represented by the avatar of a famous 2D Japanese character that changes his hair color each time he evolves.
	Environment:	A two-dimensional scenario showing a fighting arena, with the players' avatar on the center and other interface elements scattered across the screen.
Virtual interface	**World interface:**	A mobile phone or tablet, showing the game scenario and the character at its center, a clock, EEG device and its status.
	NF interface:	A horizontal bar at the top of the scenario shows the player's cumulative current attention level.
	Stimuli generator:	N/A.

Table 4. Demonstration of the model and its components (continuation).

Hangman BCI [Hasan and Gan, 2012]		
EEG data collection	**Sensors:**	Nine electrodes, positioned over the sensorimotor cortex.
	EEG device:	A 64+2 channel Biosemi cap.
Control interface	**BCI control:**	Motor imagery, using a LDA classifier as a initial state for a GMM algorithm.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Used to move the cursor (left and right) and select a letter in a Hangman game.
	Non-BCI:	N/A.
Game world	**Player character:**	Single player, with no avatar (the hangman is not considered a player character).
	Environment:	A 2-dimensional graphical scenario with the hangman and the possible letters.
Virtual interface	**World interface:**	PC display, showing a two-dimensional view of the virtual environment.
	NF interface:	The chosen letter and the confidence in the classification result appear in the game interface.
	Stimuli generator:	N/A.
Maze game [Botacim *et al*., 2021]		
EEG data collection	**Sensors:**	12 EEG sensors positioned at sites P7, PO7, P5, PO3, POz, PO4, P6, PO8, P8, O1, O2, and Oz.
	EEG device:	A BrainNet36 (Lynx Ltda.) device.
Control interface	**BCI control:**	SSVEP, classified using Goertzel Transform.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Each selected stimulus corresponds to one of the four cardinal directions to move the character (up, down, left, and right).
	Non-BCI:	N/A.
Game world	**Player character:**	A 2D robot face.
	Environment:	A flat two-dimensional maze.
Virtual interface	**World interface:**	A mobile device, showing a top-down view of the 2D maze.
	NF interface:	The direction of movement of the character indicates the chosen stimulus.
	Stimuli generator:	Four targets in the mobile device's screen, alternating between black and green at different frequencies.
MindBalance [Lalor *et al*., 2005]		
EEG data collection	**Sensors:**	Two silver chloride scalp electrodes, placed at positions O1 and O2.
	EEG device:	Biopac biopotential amplifiers.
Control interface	**BCI control:**	SSVEP, using two PSD estimation methods: squared 4-second FFT, and FFT of autocorrelation.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	The SSVEP command is used to choose the direction of the character movement (left or right) to regain balance in a tightrope.
	Non-BCI:	N/A.
Game world	**Player character:**	Single player, controlling a three-dimensional humanoid-like creature.
	Environment:	A virtual, three-dimensional scenario with a platform and a tightrope.
Virtual interface	**World interface:**	PC monitor display, with a 3D view of the environment and a third-person view of the character facing the camera.
	NF interface:	The character animation serves as feedback of the selected movement direction. Auditive feedback is also provided.
	Stimuli generator:	Embedded in the game screen. Two squares with checkerboard patterns flashing at two different frequencies (17Hz and 20Hz) to elicit SSVEP responses.
MindGame [Finke *et al*., 2009]		
EEG data collection	**Sensors:**	10 electrodes placed over the parietal and occipital regions.
	EEG device:	A Mindset24 EEG amplifier.
Control interface	**BCI control:**	P300, using PCA as method for feature extraction and FLDA as classifier.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Used to select a target tree in the game world. The player must reach all trees to win the game.
	Non-BCI:	N/A.
Game world	**Player character:**	Single player, controlling a two-dimensional cat avatar.
	Environment:	A virtual, 3D room with a checkerboard-styled floor and 2-dimensional trees.
Virtual interface	**World interface:**	A display, showing the whole scenario and a third-person view of the character.
	NF interface:	The direction and number of steps of the character serves as feedback for the selected target.
	Stimuli generator:	Each target tree in the game world also serves as stimulus, flashing consecutively.
MindGomoku [Li *et al*., 2021]		
EEG data collection	**Sensors:**	A 32-channel Electro-Cap, using all electrodes except A1 and A2.
	EEG device:	SynAmps2 amplifiers.
Control interface	**BCI control:**	P300, classified using a simplified Bayesian convolutional neural network.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Employed to select a 2D coordinate in a two-step process to place a piece in a Gomoku board.
	Non-BCI:	N/A.
Game world	**Player character:**	A single player, with no in-game avatar. The player's pieces may be considered their representation on the game board.
	Environment:	A virtual, two-dimensional graphical interface divided into two halves, one for displaying the P300 selection screen, and another for the game board.
Virtual interface	**World interface:**	A standard computer screen displaying the virtual environment.
	NF interface:	The current chosen coordinates are visually presented on the game interface, expressed through a letter and a number, corresponding to the position of the piece to be placed on the board.
	Stimuli generator:	Two grids displayed in sequence, one showing letters from 'A' to 'M', followed by the other showing digits from '0' to '9', with each symbol flashing randomly to serve as a P300 speller.
Mental War [Vasiljevic *et al*., 2018a]		
EEG data collection	**Sensors:**	A single dry electrode, positioned at site Fp1.
	EEG device:	A NeuroSky MindWave.
Control interface	**BCI control:**	Attention level, directly measured using the MindWave's eSense metric.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	The intensity of the attention metric is directly proportional to the force that the character uses to push a rope in a tug-of-war match.
	Non-BCI:	N/A.
Game world	**Player character:**	Single player, represented by a human cartoon avatar.
	Environment:	A 2-dimensional graphical scenario that changes according to the game's difficulty.
Virtual interface	**World interface:**	A PC monitor display, showing a two-dimensional view of the world and a third-person view of the player character.
	NF interface:	A vertical bar embedded in the game interface, showing the player's current attention level.
	Stimuli generator:	N/A.
Mind the Sheep! [Obbink *et al*., 2012]		
EEG data collection	**Sensors:**	Five electrodes, positioned at sites PO3, O1, Oz, O2, and PO4.
	EEG device:	A Biosemi ActiveTwo system.
Control interface	**BCI control:**	SSVEP, using a canonical correlation analysis algorithm.
	Non-BCI control:	Mouse.
Control mechanics	**BCI:**	Used to select a target dog in the game world.
	Non-BCI:	Used to point to the location to which the selected dog must move.
Game world	**Player character:**	Several dogs from the game world serve as player-controllable characters.
	Environment:	A virtual playground representing a meadow, with obstacles and fences.
Virtual interface	**World interface:**	A PC LCD monitor screen, with a top-down view of the game world.
	NF interface:	A circle around the selected dog serves as feedback for the classification result.
	Stimuli generator:	Each of the three possible target dog flashes simultaneously at 7.5, 10, and 12 Hz.
Motion-onset evoked potential (MoEP) infinite runner [Amini and Shalchyan, 2023]		
EEG data collection	**Sensors:**	12 electrodes, placed at sites Cz, TP7, CPz, TP8, P7, P3, Pz, P4, P8, O1, Oz, and O2.
	EEG device:	A 32-channel EEG-Bayamed recording device.
Control interface	**BCI control:**	Motion-onset evoked potentials, classified using various methods, including Stepwise Linear Discriminant Analysis (LDA), LASSO-LDA and spatial-temporal discriminant analysis.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	The player must choose one amongst five lanes to move their character. The path is chosen by focusing on the target stimuli above each lane.
	Non-BCI:	N/A.
Game world	**Player character:**	A single player represented by a three-dimensional adult human avatar.
	Environment:	A virtual, three-dimensional road with a flat two-dimensional image on the background.
Virtual interface	**World interface:**	A standard computer display showing a third-person view of the character running on the scenario.
	NF interface:	Embedded in the game interface. Each running lane has an arrow indicating the selected choice after classification.
	Stimuli generator:	Five geometric objects, one above each possible choice of running lane, which generate stimuli based on four paradigms for MoEP: translation, rotation, expansion, and contraction.
Motor imagery infinite runner [Prapas *et al*., 2023]		
EEG data collection	**Sensors:**	Four dry electrodes positioned at TP9, AF7, AF8, and TP10.
	EEG device:	A Muse 2 EEG headband.
Control interface	**BCI control:**	Left-right hand motor imagery and blinking, classified using a multi-layer perceptron with OpenViBE.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	The left and right imagined movements of the hand makes that player's character slide to the left or to the right, respectively. Blinking makes the character jump.
	Non-BCI:	N/A.
Game world	**Player character:**	A single player controlling an anthropomorphized fox-like animal avatar using an armour, sword and shield.
	Environment:	A three-dimensional continuous street with coins scattered across.
Virtual interface	**World interface:**	A computer monitor, showing a third-person, three-dimensional, top-down back view of the character.
	NF interface:	The movement of the character serves as indicator of the classified command.
	Stimuli generator:	N/A.

Table 5. Demonstration of the model and its components (continuation).

NeuroBall [Paszkiel *et al.*, 2021]		
EEG data collection	**Sensors:**	14 saline electrodes, positioned at sites AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1, O2, and referenced to two ground electrodes at P3 and P4.
	EEG device:	An Emotiv Epoc+.
Control interface	**BCI control:**	Concentration, obtained using the Emotiv's Cognitiv Suit.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	The player must concentrate and imagine cognitive functions (e.g., "push") to control their avatar in the game environment.
	Non-BCI:	N/A.
Game world	**Player character:**	A single player controlling a three-dimensional red ball.
	Environment:	A three-dimensional virtual scenario simulating a plains environment, surrounded by a fence, and divided into four levels, containing wood boards, obstacles, rocks, vegetation, and mountains.
Virtual interface	**World interface:**	A standard computer monitor, showing a third-person view of the red ball.
	NF interface:	During training, the Emotiv's Control Panel provides visual feedback using a virtual cube. During game playing, the player's avatar movement serves as feedback for the EEG-activated action.
	Stimuli generator:	N/A.
Neurofeedback Space [Machado *et al.*, 2019]		
EEG data collection	**Sensors:**	Seven dry EEG sensors positioned at sites F3, F4, C3, Cz, C4, P3, and P4.
	EEG device:	A Quick-20 (Cognionics, USA) EEG wireless headset.
Control interface	**BCI control:**	Attention, acquired using spectral features with a SVM classifier.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	The player increases or decreases the speed of the character by 10% each second based on their attention state.
	Non-BCI:	N/A.
Game world	**Player character:**	A 2D spaceship.
	Environment:	A two-dimensional scenario representing space, with stars and coins.
Virtual interface	**World interface:**	A computer monitor, showing a top-down view of the spaceship in space.
	NF interface:	The increase or decrease in speed of the spaceship indicates the player's attentional state.
	Stimuli generator:	N/A.
Pinball [Tangermann *et al.*, 2008]		
EEG data collection	**Sensors:**	64 sensors (implied by the number of channels).
	EEG device:	Not informed.
Control interface	**BCI control:**	Motor imagery, with CSP filters to extract power features to a LDA classifier.
	Non-BCI control:	A lever.
Control mechanics	**BCI:**	A low-level command is used to control the left and right paddles of a pinball machine, using the respective imagined movement (left hand or right hand).
	Non-BCI:	The player must pull the lever to launch a new ball.
Game world	**Player character:**	Single player, which controls two paddles.
	Environment:	A physical pinball machine.
Virtual interface	**World interface:**	The machine itself serves as a physical, auditory, and visual interface.
	NF interface:	The movement of the paddles serve as feedback for the classified command.
	Stimuli generator:	N/A.
Spacecraft game [Parafita *et al.*, 2013]		
EEG data collection	**Sensors:**	12 passive electrodes, placed at positions Fz, Cz, CPz, C3, C4, Pz, POz, P3, P4, OZ, P07, and P08.
	EEG device:	A g.USBamp amplifier, sampling EEG signals at a 256 Hz rate and applying a 0.1–30 Hz band-pass filter and a 50 Hz notch filter.
Control interface	**BCI control:**	SSVEP, classified using a correlation method using phase tagging with a reference signal.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Focusing on the left or right stimuli moves the player's avatar to the corresponding direction, which aims at avoiding obstacles.
	Non-BCI:	N/A.
Game world	**Player character:**	A spacecraft controlled by a single player.
	Environment:	A virtual three-dimensional space environment with a long lane with obstacles, the player's avatar and a black background.
Virtual interface	**World interface:**	A laptop screen showing a third-person view of the player's avatar from the back, along with two arrows on the sides for SSVEP stimulation.
	NF interface:	The displacement of the spacecraft to the corresponding direction serves as feedback regarding the classification decision.
	Stimuli generator:	Two arrows, embedded in the game interface, one pointing to the left and the other to the right, flickering at the same frequency within the 3–5 Hz with an offset of 180 degrees.
Thinking Penguin [Leeb *et al.*, 2013]		
EEG data collection	**Sensors:**	A cap with five electrodes, placed at position Cz and four orthogonal sites.
	EEG device:	A 16-channel g.Tec biosignal amplifier.
Control interface	**BCI control:**	Motor imagery, detected using a LDA classifier for ERS and ERD frequency bands.
	Non-BCI control:	A joystick (and a push-button in non-BCI gameplay).
Control mechanics	**BCI:**	Used to make the character jump to catch fish.
	Non-BCI:	Controls the left-right movement of the character.
Game world	**Player character:**	A three-dimensional penguin avatar.
	Environment:	A virtual, three-dimensional snowy mountain.
Virtual interface	**World interface:**	A 3D virtual reality environment, projected in the walls of a four-sided room.
	NF interface:	The jumping of the penguin serves as feedback for the detection of the desired motor imagery.
	Stimuli generator:	N/A.
Tower defence game [van Vliet *et al.*, 2012]		
EEG data collection	**Sensors:**	Up to 14 electrodes.
	EEG device:	Emotiv Epoc, with 14 passive, saline electrodes, or an ActiCap system with eight channels sampled with active sensors.
Control interface	**BCI control:**	SSVEP, classified using a correlation threshold with a Stimulus-Locked Inter-trace Correlation algorithm.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Used to choose a location for placing towers in a tower defence game. Each location is highlighted in sequence, and the player must focus on the target stimuli when the chosen location is selected.
	Non-BCI:	N/A.
Game world	**Player character:**	A single player with no in-game avatar. The player is represented by the towers they place in the game map.
	Environment:	A virtual, three-dimensional arena composed of paths in which the enemies will walk through, and pre-determined locations that the player can place towers to attack the enemies.
Virtual interface	**World interface:**	A computer screen showing a top-down view of the game environment, and other information regarding the game status.
	NF interface:	A horizontal bar at the top of the game shows the classification output of the classifier.
	Stimuli generator:	A square in the game interface that flashes at a given frequency during the tower placing phase of the game.
VR Maze [Koo *et al.*, 2015]		
EEG data collection	**Sensors:**	Eight electrodes, positioned at the occipital-parietal region.
	EEG device:	A g.Tec g.MOBIlab+ device.
Control interface	**BCI control:**	SSVEP, detected using a canonical correlation analysis algorithm.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Used to select a target tile destination for the player to move.
	Non-BCI:	N/A.
Game world	**Player character:**	A single player controlling a sphere.
	Environment:	A virtual, three-dimensional grid, with objects or empty spaces in each tile.
Virtual interface	**World interface:**	A monitor or an Oculus Rift head-mounted virtual reality device.
	NF interface:	The movement of the sphere in the grid serves as feedback for the selected tile.
	Stimuli generator:	Each tile perpendicular to the sphere flashes at a different frequency as stimulus.
Wild Jumper [Gonçalves *et al.*, 2023]		
EEG data collection	**Sensors:**	A single dry electrode at position Fp1.
	EEG device:	A NeuroSky MindWave device.
Control interface	**BCI control:**	Concentration and meditation levels, measured using the NeuroSky's eSense metrics.
	Non-BCI control:	Left/right controls (presumably with a keyboard).
Control mechanics	**BCI:**	Concentration and meditation levels control the overall difficulty of the game, while also controlling the horizontal and vertical speed of the character.
	Non-BCI:	Moves the character horizontally.
Game world	**Player character:**	A single player controlling male human character.
	Environment:	A three-dimensional continuous street with various obstacles and coins scattered across.
Virtual interface	**World interface:**	A monitor, showing a third-person, three-dimensional, top-down back view of the character.
	NF interface:	The speed of the character, number of obstacles and their spacing between each other serves as indicator of the current levels of attention and/or meditation.
	Stimuli generator:	N/A.
Zen Cat [Vasiljevic *et al.*, 2018a]		
EEG data collection	**Sensors:**	A dry electrode at position Fp1.
	EEG device:	A NeuroSky MindWave device.
Control interface	**BCI control:**	Meditation, using the EEG device's meditation score.
	Non-BCI control:	N/A.
Control mechanics	**BCI:**	Meditating above a given threshold, which depends on the difficulty and player position, makes the player's avatar levitate towards the top of the vertical scenario.
	Non-BCI:	N/A.
Game world	**Player character:**	A two-dimensional cat cartoon avatar.
	Environment:	Several different two-dimensional scenarios that depends on the current difficulty and player position. Each scenario starts at the ground, and goes up to the sky and universe.
Virtual interface	**World interface:**	A computer screen, showing the players' avatar and the 2D scenario from the front.
	NF interface:	A vertical bar in the game interface shows the player's current average meditation.
	Stimuli generator:	N/A.

and its extensions (i.e., 10-10 and 10-5), more general and descriptive values can also be employed, that is, over which cerebral lobe the sensors are placed, or the standard placement of a given head-mounted device.

For the EEG device, important attributes that can be described are the brand or model and manufacturer of the device, which can be further complemented by pre-processing capabilities, for example, band-pass filters and sampling rate. Note that although some consumer-grade EEG devices have a fixed number of sensors, not all of them were necessarily employed in the collected games, and thus were described in all of their extensions in both sub-components. When all sensors are employed, their location can be omitted if a default spatial configuration is guaranteed. A summary of these attributes is shown in Figure 7.

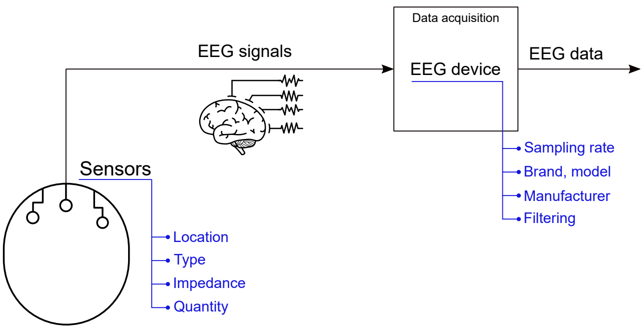

Figure 7. Recurring descriptive values of the *EEG Data Collection* component.

4.1.2 Control Interface

For BCI controls, it may be relevant to describe the employed control signal, its nature, and how it was processed. It may also be important to distinguish between open and closed-box implementation of the control signals, since consumer-grade devices usually provide proprietary metrics for endogenous cognitive-based commands. For non-BCI controls, a detailed description depends on the complexity of the employed control. For example, some games employed mouse and keyboard to control the movement of a character. This movement can be performed in many ways, although it is common to use the mouse to aim and trigger specific actions, while the keyboard is employed for directional controls.

The recurring descriptive values of this component are listed in Figure 8.

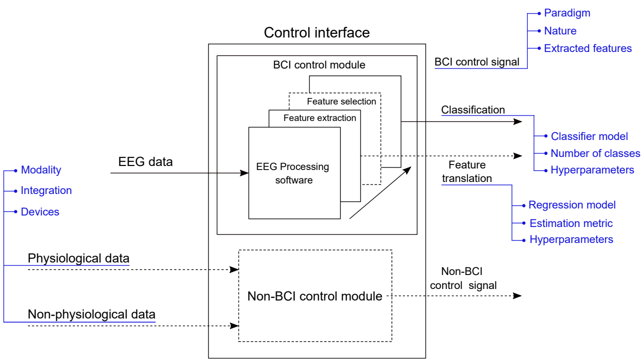

Figure 8. Recurring descriptive values for the *Control Interface* component.

4.1.3 Control Mechanics

Although the control mechanics varies depending on the game genre, employed control signal and platform, a few recurring values were observed for the collected studies and related works. For the dependence on the control signal, exogenous controls are usually employed for selecting one amongst several targets. Motor imagery is usually employed for one-dimensional movement, with few occurrences of mental imagery also being used for one- or two-dimensional controls. Sustained attention and other cognitive-based tasks were usually employed for reaching a target threshold value for a given period of time and trigger an action, such as scoring, reaching the next stage or one-dimensional movement. Emotion recognition was only employed for passive dynamic difficulty adjustment. Non-BCI controls also depends on the specific controller device, although the target mechanics are the same as the BCI ones, as they objectively controls the same elements in the game world through different means. The identified control mechanics for both BCI and non-BCI controls are listed in Figure 9.

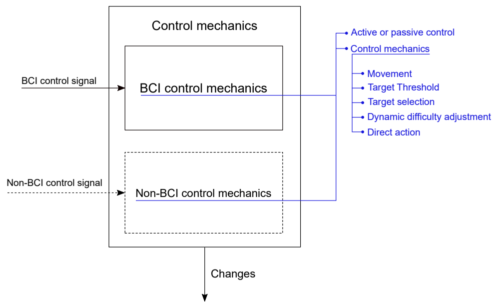

Figure 9. Recurring descriptive values for the *Control Mechanics* component.

4.1.4 Game World

The description of the game world depends on the emphasis that one aims to achieve. A complete description would include the number and description of each player's characters, possible non-playable characters and possible game objects and scenario. For the demonstration of the player's character, the focus was on describing the number of players and how they are represented in the game's virtual world. This included dimensionality and overall characteristics of the player's avatar, or whether there is none. For the environment, the dimensionality and overall description of the scenario and its objects were also emphasized. User interface and heads-up display (HUD) elements may also be described accordingly. Figure 10 represents these characteristics.

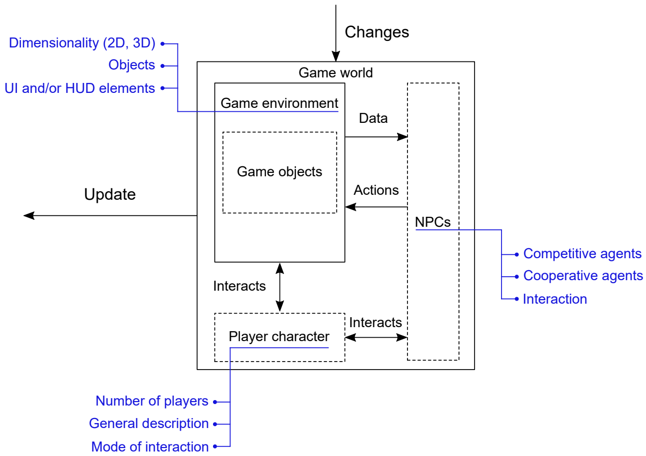

Figure 10. Recurring descriptive values for the *Game World* component.

4.1.5 *Virtual Interface*

Since the virtual interface is the mean by which the player receives feedback regarding the game status, its description tends to be more objective, in the sense of describing the game platform and visualization means. Although not shown in the examples, this virtual interface for the game world could be composed solely of haptic or auditive elements. The vast majority of games employ either a two- or three-dimensional graphics interface, with a predominance of two-dimensional games. There is an increasing number of games being developed for three-dimensional graphics, especially with the use of game engines that have libraries for commonly employed EEG devices. This also include games using exogenous control signals, such as SSVEP and P300, which depends on the visualization channel to be evoked.

The neurofeedback interface, although usually given explicitly with a user interface element, was also provided in an implicit manner through the player avatar and other game objects, including the cases in which the BCI control was made in a passive paradigm. For the stimuli generation, although there are examples of games using external generators, the vast majority of exogenous-based games found in this study embedded this generation in game elements, either specific or imbued in the scenario amongst other game objects. Figure 11 shows a summary of the attributes of these interfaces and stimuli generators. Note that some attributes, for example, size, color, shape, may only be applied to visual-based stimulus.

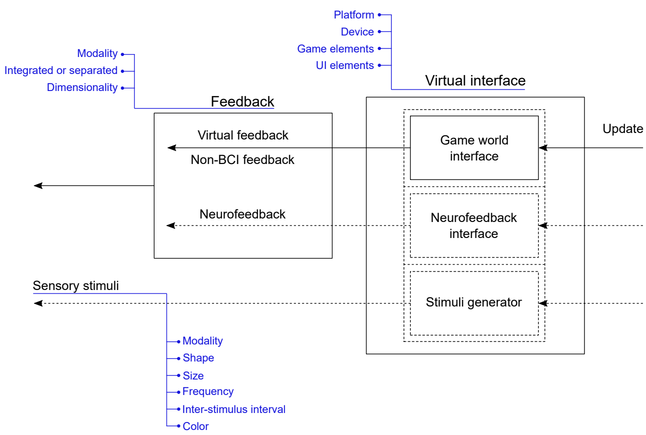

Figure 11. Recurring descriptive values for the *Virtual Interface* component.

5 Discussion

For answering the research questions proposed in Section 1, we discuss the proposed model in relation to the collected studies, its demonstration, the comparison to related studies, and its current limitations. For RQ1, we showed how the integration of both BCI processing application and game system could be achieved by the derivation process of the model, that is, by simplifying the classical BCI neurofeedback loop and considering it as a single entity encapsulating an application. By instantiating this application as a game, we showed how both the functional and structural components of an unified BCI game system can be represented by performing the inverse process, that is, going from this overly simplified scheme and detail each of its parts considering the theoretical backgrounds of both BCI and games.

This derivation process, along with the detailing of each component shown in the demonstration, are also important in the context of RQ2, as it shows that these components can be represented and described simultaneously, regardless of system platform, EEG processing and classification algorithms, control signal, hybrid controls or game genre, for example. The principles that guided the derivation of the model also helped in defining the recurring objective and descriptive values for each of these components, as shown in Section 4.1.

In this sense, the demonstration of the model wielded interesting results about its ability to represent and compare games from the literature. The individual representation of each game gives an overview of its contents and allow for the extraction of its concept and design from this description. The open aspect of the description of each component, as opposed to more closed and pre-defined classification values, also gives the researcher or developer more freedom to emphasize on specific aspects that s/he finds pertinent. Thus, although a brief summary of each component was provided for each game for the purpose of demonstrating its representativeness, a more detailed description is also possible.

For RQ3, as the proposed model is based on the classic neurofeedback loop and described the traditional EEG signal processing steps, its BCI aspects resembles most representative schemes of EEG-based systems, as they were the base for its construction and derivation process. It has the advantage, however, of also representing the details about the game itself, as both aspects are seen as only one entity, in contrast with other BCI models and representations in which the BCI implementation is taken as a separate software or hardware, or in which the game (or any other application) is abstracted and only receives the control signal to consume. The downside of this generalist approach for the representation of games is that some details about its implementation (including the implementation of the BCI module) may be lost, for example, in which platform the game is intended to run, its genre, the details of the feature extraction and translation steps and so on.

However, although not exhaustively shown in the demonstration, some specific details about the signal processing algorithm could also be represented in the *BCI Control* component depending on the goals of the researcher, as shown in the summary of recurring descriptive values. Information about the pre-processing steps (e.g., filters and de-noising techniques) or the feature extraction/classification algorithms could help in the comparison of different implementations for the detection and employment of the same neural mechanism. The same could be applied to game-related components, such as details about the game architecture (e.g., local or networked) or the game genre, which can be described implicitly through the appropriate components.

In the same sense, the values obtained from the demonstration show that it is possible to group common classified values, for example, the employed EEG device or the virtual interface, which seem to have a limited number of possible values, at least for atomic information, such as whether the interface is virtual or physical; auditive, somatosensory or graphical; and its dimensions. This could allow not only for a pre-defined list of classification values for such specific components, but also to classification schemes based on these values, such as the CoDIS Taxonomy [Vasiljevic and de Miranda, 2024a], developed using the model's components as its theoretical foundation. This taxonomy separates these classification values in a more direct fashion, as opposed to the descriptive nature of the model's components, allowing for an objective comparison of games from the literature. However, as games are fundamentally different from one another, open descriptions are still required to fully describe the concept of the game, making both the model and the taxonomy as complementary descriptive schemes.

Lastly, it is also important to note that the proposed model, although not directly a system architecture framework, can be used as a base for the development of new EEG-controlled games and their software architecture, as its components and their connections are an abstraction and can be instantiated in numerous ways, using any supported and available technology. A similar approach has been employed, for example, by Sung *et al.* [2012], in which the authors built a framework for EEG-based serious games based on their proposed model. The model itself was built around both the functional and structural components of existing games, thus it mirrors some of its system architecture.

We envision this design and implementation application of the model as an incremental and comparative process, in the sense of using it to describe related studies, comparing the instantiation values for their components (e.g., which sensors were employed, using which EEG device, to provide which BCI controls, etc.), and adapting these values for the task at hand. For example, one could aim at conduct an experiment employing an EEG-controlled game using attention as a secondary control (e.g., for controlling the difficulty of the game). A first step would be to select games with Attention as *Control Interface / BCI Control*, non-empty *Control Interface / Non-BCI*, and with *Control Mechanics / BCI* used for controlling game difficulty, either passively or actively. If no existing games would be sufficient for one's goal, a new game could be developed by instantiating the other values of the model, including the components described in Table 1 and the category values detailed in Section 4.1.

5.1 Limitations

The demonstration of the model also showed some of its limitations. As aforementioned, the first limitation is related to the extension of the described data, which allows for an overview of the game and how it is played with the BCI controls, but may lack some details about the employed signal processing algorithm and the game, such as its platform and number of players, which have no specific component to represent them and must be implied through the description of related components. The player(s) from Fig. 6, for example, could be a component itself, representing the number of players and the target audience for the game, since the information regarding number of players and their mode of interaction are described separately and indirectly as part of the *Player Character* component. This approach was not employed in the current model as it is intended to represent EEG-controlled games, and the player is technically not a part of the game itself. However, although the model could be expanded to represent such details more precisely, it could be argued that the player should be considered a component of the model, instead of an element that participates in its function.

Another limitation is related to the independence of each component in relation to each other. Some components appear to provide less contribution to the general understanding of the game without the complement of other components; for example, the *Player Character* component provides a very specific information that, although generally necessary for the context of the *Control Mechanics* and the *Virtual Interface*, could be implicitly represented through other components. Merging these information into other general components could, however, increase the difficulty in extracting specific data from each game in order to compare them (or to describe the concept of a new game), as too much information would be gathered into a single component.

Finally, although the proposed model was developed based on an extensive analysis of EEG-based games from the literature and its demonstration based on methods from related works, it could be further validated with experts from the field. Such evaluations, conducted with specialists in BCI, game design and user experience, could assess the clarity, completeness and practical relevance of the model when applied to different design and research contexts.

6 Conclusion

This work presented a general and unified model for EEG-based BCI-controlled games. The model is also integrated, as it is intended to represent such games by describing their functional, structural and abstract components, the connections between them and their constituting parts in a single representational scheme. The proposed model unifies concepts and components from both BCI and games, which were collected, analysed, refined and specialized from various related models and classification schemes from both fields.

To demonstrate its usefulness and representativeness, a set of EEG-based BCI games from the literature was described using each of the components from the model. The demonstration showed that the model is capable of representing aspects both from the classic EEG signal processing steps based on neurofeedback applications, and from the game itself, providing an overview of the game, how the player interacts with it and how it is played using both the BCI and non-BCI controls. We also summarized common description attributes and characteristics of the collected games, showing possible default values for instantiating each component in a systematic manner, which may serve as base for future classification and standard EEG-based game descriptions.

The principles that guided the construction of the model allow for its adaptation to different contexts and applications, and for it to evolve and expand with new components depending on the needs of the researcher and on the context it is inserted. It is expected that, as the model evolves, it will be able to represent not only EEG-controlled games, but also studies involving those games and the contexts in which they are being applied, facilitating its employment in the comparison of different BCI-based studies, for example, in meta-analyses for comparing the performance of different signal processing algorithms for the classification of EEG signals, or the effects of playing EEG-based serious games in subjects for clinical trials. This adaptability and expansion can also guide researchers and developers in exploring new combinations of BCI and non-BCI controls, leading to novel and more effective interaction between players and game systems.

In the same sense, the proposed model can also help researchers in the design and development of new EEG-controlled games, and guide future studies that employ those games. The separation of components and the representation of their structure and functions can also aid in identifying and isolating possible focus points for improvement, especially considering system performance, interaction design and user privacy. Future works, in this sense, involve using the model as a base for the design and development of new EEG-controlled games, as well as conducting and comparing primary studies involving those games, while also validating these designs with specialists. In addition, a more general system architecture for EEG-based games could be developed using the model as foundation.

Declarations

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Authors' Contributions

The authors contributions, following the CRediT taxonomy, are as follows: Gabriel Alves Mendes Vasiljevic (Conceptualization, Data curation, Formal Analysis, Investigation, Visualization, Methodology, Writing – original draft), Leonardo Cunha de Miranda (Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing).

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The source works for components, derived attributes and recurring classification values are available as supplementary files.

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